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EEG data understanding for Epilepsy Classification

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VEDAVATI BHANDARI

Research Scholar

Under the Guidance of

Dr. MANJAIAH D.H

Senior Professor

Department of Post-Graduate Studies and Research in Computer Science Mangalore University Mangalagangotri-574199

Karnataka, India

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ABSTRACT

A general category of the brain disorder is epilepsy that can result in the unexpected changes in the human behaviour. Epilepsy can be an outcome of stroke, old brain injuries, and brain-related disorders or because of the existence of brain tumor cells. If the epilepsy is detected in the starting stages, various cases are treated by medicine and do not need surgery. The epilepsy is detected by taking the seizure as a symptom. The electronic signals transmitted by the brain are referred to as the seizure. The damages can be decreased if the seizure is identified in the starting phase, resulting in a good cure for the individual troubled by the epilepsy. This neurological disease is detected via the manual understanding and the optimal examination of the EEG signals. Some of the enhancements in deep learning tasks lead to rectify the complex issue. An approach for detecting the seizure is employed for identifying the brain's pre-ictal stage presented in the individual before being troubled by the seizures. A model to recognize the seizure's existence without the sick person's presence is capable of precisely identifying the seizures from the data source including a high amount of data. This kind of model has discovered its developments in the real-world situations. However, designing certain kinds that can simply change to the inter-subject modification in the EEG data is not considered much. To accomplish the goal of detecting the epilepsy, the model can identify the epilepsy's existence from the epileptic EEG signals that still a helpful component. Moreover, the present deep learning tasks not employed the EEG information for identification of epileptic seizures. Hence, there is an urgent requirement for automatic identification of the epileptic seizures in the medical sector. This offered thesis includes three powerful contributions for recognizing the epileptic seizures automatically by adopting the advanced optimization and the deep learning tasks. In the initial contribution, the epileptic seizure is identified by employing the I-ELM. Initially, the EEG signals are obtained from the benchmark resources and then they are involved with the pre-processing task with the support of STFT. After that, the DWT is helped to perform the signal decomposition. Then, by influencing the "spatial and temporal" approaches, the feature extraction is performed for the given decomposed signal. In order to diminish the length of the feature for handling the complexity of training and improving the detection functionality, a new advanced optimization approach named M-TSA is utilized. The acquired features are given to the I-ELM network that including the DNN and LSTM classifiers. The outcome of the I-ELM network is attained from the high-ranking method

by employing the suggested M-TSA. Finally, the seizure-identified outcome is obtained and contrasted with the other traditional tasks. During the second contribution, the detection of seizures is performed with the support of new classification and the feature extraction tasks. At first, the attained signals are pre-processed, and then by adopting the DWT and EMD, the signal decomposition is conducted. After that, the selection of attributes is conducted by employing the LDA and PCA. With these elected attributes, an improvement is performed with the task of "weighted feature selection" in that the weight is tuned with the aid of new modified approach called J-CSO. After that, the J-CSO-aided I-ELM network is presented in the identification task. In the end, the seizure-identified outcome is attained and the solutions are compared with the classical seizure detection tasks.

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LIST OF ABBREVATION AND SYMBOLS

ABBRIVATION	DISCRAPTION
DNN Deep neural Network	Deep neural Network
DWT	Discreate wavelet transformation
EEG	Electroencepologram
EMD	Empirical mode decomposition
FC	Fuzzy Classification
FDR	False Discovery Rate
FNR	False Negative Rate
FPR	False Positive Rate
GWO	Grey Wolf Optimization (GWO)
IELM	IMPROVED ENSEMBLE LEARNING MODEL
JCSO	Jaya-Cat swarm optimization
LDA	Linear Discriminant Analysis
LSTM	Long Short-term Memory
MCC	Mathew's correlation coefficient
MTSA	Modified Tunicate Swarm Optimization
NPV	Negative Predictive Value Specifici
PCA	Principal Component Analysis
PSD	Power Spectral Density
PSO	particle Swarm Optimization
STFT	Short-Time Fourier Transform technique
WOA	Whale Optimization Algorithm

CHAPTER 1
INTRODUCTION

1.1 Background

Majority people around the globe are affected by epilepsy, which is the regular neurological disorderliness. Seizures have the chance to form on the circumstances or host attributes. The unforeseen and sudden seizures formed for the people who suffered from epilepsy. During this phase, it is difficult to protect themselves, and are in danger of injury, suffocation, and death because of the traffic and fainting accidents. But also, the major reason for the disease is currently unknown. The most of the epilepsy seizure activities can be treated medically. At the time of seizure, patients with epilepsy disease are at risk, and the result causes convulsions, uncontrollable movement, and consciousness loss. This causes major injuries and sometimes it causes death [1]. At the time, the human brain performed the cognitive task, the EEG clinical tool was used to collect the images of brain. By introducing the electrodes on the head scalp, the EEG gathered images of the patient. This helps to record the brain's electro-activity along with the scalp. Several signal properties are detected by the process of DWT in which the wavelet transmits the single sample captured from the feature of the signal or image. It captures all the information based on the location and frequency. By examination, the epilepsy can be diagnosed clinically through EEG, CT, MEG, MRI, and PET. In detecting epilepsy, EEG position a significant role as it calculates the variation in voltage which differentiates among the electrodes also with the scale subject by currents flowing sense ionic with the neurons in the brain. This offers spatial and temporal data about the brain. For an accurate diagnosis, several days of EEG monitoring are necessary to recognize epileptic seizures [2]. EEG monitoring manually is so difficult. Hence, a long-term monitoring procedure for a reliable identification technique of seizure is needed for the treatment of epileptic seizures. Hence it is important for the medical staff in the process of seizure activity for analyzing the epileptic patient. Engaging and interacting with the patients helps to monitor and create awareness among the patients. This helps to estimate the seizure and recognize the position of the affected area in the brain. The automatic seizure detection model alerts medical professionals and allows them to take immediate medical inventions. In many of the researches, multiple detection algorithms for epileptiform EEG data are developed. The existing models for detecting seizures use hand-engineered techniques for feature extraction from the EEG signals. The examination's importance is highlighted by many

types of research based on the brain connectivity function in successful seizure localization and detection. Based on the electrode placement location, EEGs are segmented into scalp recording and intracranial. It is non-invasively recorded by the scalp EEG and hence more popular and most used clinical application. After many attempts, seizure detection has been made to introduce the algorithm by utilizing both intracranial and scalp EEG [3]. But still, it is necessary to have, an automated reliable algorithm with minimum computation difficulties for real-time applications. Between the accuracy, complexity, and efficiency, better compromise is needed based on the generic wavelet decomposition applications. The research uses a developed technique to classify the EEG data for high-dimensional and large-scale data processing. This helps to focus on recognizing the epileptic seizure.

1.2 Epileptic Seizures

Epilepsy is not a single disorder, but it is a collection of family disorder conditions, which increase the predisposition to seizures. An epileptic seizure is the transient, which is delimited in time, with the correct initial and end. The most common characteristic of epileptic seizure is the enhanced abnormal synchrony of neurons. Without ascribing towards the brain epileptic seizure is operationally challenging. Epilepsy is based on the same patient with multiple causes is considered to be multiple epileptic seizures. There are multiple methods for long-term EEG monitoring and they are available for recording the epileptic seizure much more frequently. This type of monitoring needs regular supervision by the EEG specialist.

Epilepsy is a recurrent seizure. The seizure is based on the immediate improvement of synchronous neural firing in the cerebral context or inside the brain. The seizure tends the patient to find the medical advice that defines the index seizure. The exact mechanism that leads to the occurrence of elliptic seizure is poorly understood. The procedure of seizure generation is related with uncommon neurons synchronization.

The subclinical seizure and the clinical seizure are the only EEG manifestations that are identified easily [4]. The unclassified epileptic seizure contains all the seizures that cannot be able to classify because of the incomplete data including some seizures that are classified in the broad category. A seizure related to the main clinical encumbrance and event of the selective epileptic control. During an epileptic seizure, it is difficult to demonstrate the clinical objective phenomena and subjective specification, because of the

heavy range of possible appearance. Epileptic seizure is a clinical event, in which features must be prominent symptoms. Seizure presentation is based on pattern propagation, medication, the process of confounding disease, and multiple other factors. Seizures also affect the consciousness, cognition, and sensory behavior. Epilepsy attacked patients suffer from stigma, isolation, and over-protection become the phase of the epileptic condition.

Also, the presence of seizures is based on various options like the location of onset in the brain and maturity of the brain [5]. Based on daily practice, clinical neurologists generally examined the short recording of the interictal periods. The maximum of the regular forms of the interictal period are the single or isolated spikes. Based on the isolated spike, the brain is in a clinical seizure. During the ictal period, various EEG structure is noted in the form of the rhythmical waveform of most of the frequency. The finding of the interictal provides evidence of epilepsy based on the observed epilepsy seizure.

1.2.1 Epileptic Seizure Detection using EEG Signals

Epilepsy is a neurology illness, that impact nearly many of the people regarding to the WHO. EEG plays a major part in noticing the activity of patient's brain with epilepsy and diagnosing the epilepsy. The professionals are required to evaluate the EEG recording to identify epilepsy activity. This model takes more time to process and also needs accurate diagnosis to start the antiepileptic drug therapy to minimize the risk based on the seizure-related difficulties. EEG is the widely used model to scan the non-linear electrical function of the brain nerve cells. Hence it is a valuable process for the evaluation and cure of epilepsy [6]. The analysis of the EEG signal which involves the sharp and spike waves is hard for the time of seizure but also for the short time before the seizures. In general, the epileptic activity detection needed human monitoring of the EEG reporting, which required more time to finish the procedure. Classical technique for recognizing and separating the EEG epileptic seizure contains the following steps. Block diagram for the classification and detection shown in Figure 1.1

- EEG preprocessing
- Evaluation of EEG signal based on time or frequency
- Feature extraction to find the seizure activity
- Classification based on the extracted feature

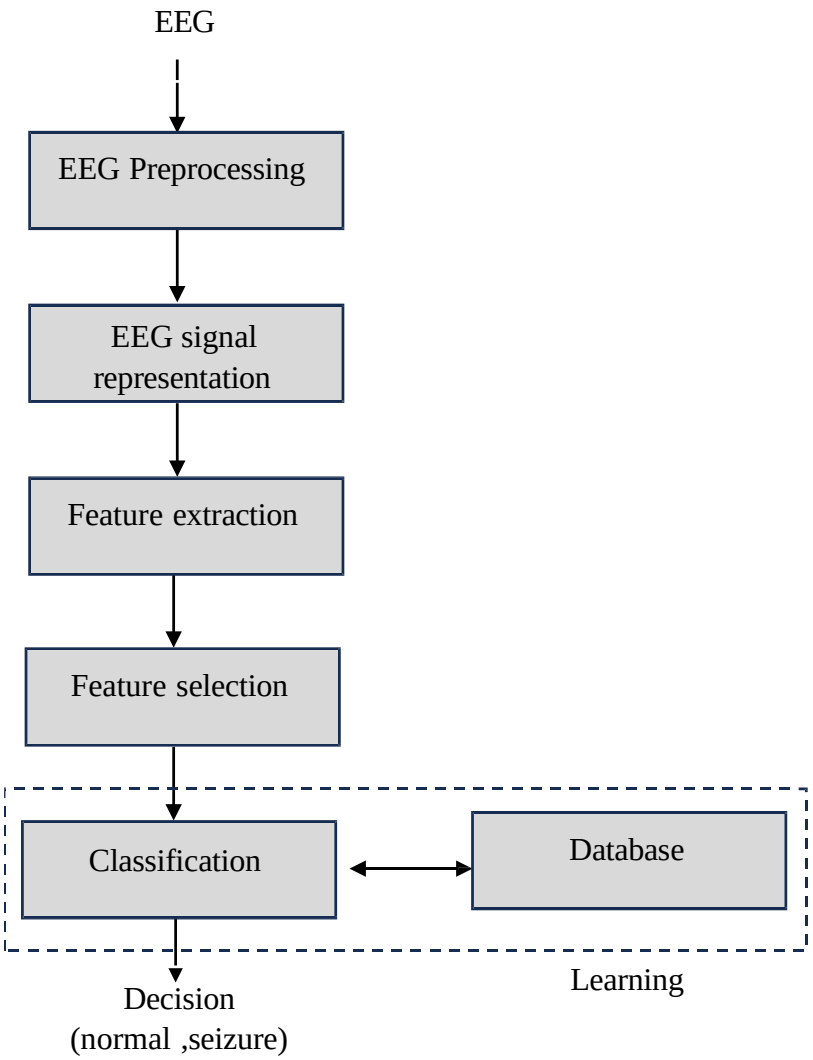

Figure 1.1: Block diagram for the classification and detection for EEG epileptic seizure

It is recommended to analyse the characteristics of the research by evaluating the recorded signs of EEG of epileptic seizures. During seizures, the EEG signal recorded contains various forms of signals from EEG from the non-epileptic person. Therefore, the EEG evaluation started to vary the epileptic from general information and to change the multiple phases of the seizure. The seizure changes the preceding by identifying the EEG changes and it is possible to forecast the onset of the epileptic seizure. The automated system is needed for the prediction system which views the inter-ictal, normal, and pre-ictal phases. In the normal phase, the healthy person's EEG data are taken and the pre-ictal phase defines to the preceding variation in the EEG for the seizure. Finally, the inter-ictal phase defines the EEG changes on the seizure. There are two major considerations in the detection system. The first set of considerations is the type of feature to be extracted from the EEG signal, based on the feature extraction technique [7]. The further recommendation is the sort of evaluation model to be used on the feature extraction to find the phase which

is the detection technique. Epilepsy occurs when someone has an epileptic seizure which defines the pathologic and enduring capacity to have recurrent seizures. Epilepsy is considered to be resolved based on the following circumstances.

- Age-based epilepsy syndrome patient who is older than the age in which the syndrome is activated.
- The patient of less than or equal to 10 years with seizures has been off all medication for five years.

EEG-based seizure is the most rarely used performance that helps the neurologist. This is based on multiple factors, in which the difficulty in the epilepsy and the brain wave is the main one. The EEG signals are the statistical feature with non-stationary signals which vary between the patients over time. The next factor is the dataset quality used for the machine learning task. Other than the feature extraction, nonlinear evaluation, and frequency time of the EEG signal received known attention to identify the epileptic seizures that happen in the transition of the human brain. In addition, EEG signals are mostly non-linear and non-stationary. The EEG signal decomposes by the EMD of the intrinsic mode of the function, which has the capacity of defining the nonlinear and nonstationary process.

1.2.2 EEG Channel Selection for Epileptic Seizure Detection

While functioning head scalp based on EEG, the voltage fluctuation between two known electrodes produces the channel. Various frequency bands of five brain waves form the most useful data about the condition of the brain. Then listed the frequency band as alpha, gamma, beta, and delta. All of them coincide with various multiple and unexpected states of mind disturbances of the waveforms for instance on the epileptic seizure. To differentiate these signals, either chooses the work on the channel subset depending on the chosen criteria of work or channel-based work [8].

The channel selection approach is important for minimizing the computational cost and achieving it to form the outcome quicker and portably considered with minimum cost headsets. It helps to focus on the channel with the most data by maintaining or improving the classification accuracy. There is a potential value for the channel reduction during the seizure detection. Most of the time EEG signals have multiple channels for receiving the signal from various places on the scalp. The overfitting effect is formed from working with most of the channel generally when the channel working with the redundant.

The selection of channel is consumed to stop the thereupon and size of the structure which reduces the feature extraction computation cost and the classification. From the research it is concluded that it is possible to take the minimum set of EEG channels ranging from 10 to 30% of the whole channel, also it happened without losing more function in the detection phase. The experiment also shows that signal statics like entropy and variance can use the channel section during EEG seizure identification.

The EEG data of intracranial are recorded by the different number of channels. The more channels are taken larger the computational complexity of analyzing the data. This causes diversity in the data because there is the chance to capture irrelevant information. For the manual selection, leverage bio-medical knowledge is required [9]. Disclosing the set of channels is not possible with the significance of the subjects. It needs an experienced person to evaluate every subject to demonstrate the significant channels list about every position for the time-consuming task. The selectin of channel depends on the changes of EEG signal amplitude with the judge variance selected. Here each channel extracts seven features. When there is the maximum quantity of channels, there is less favorable in the number of subjects.

1.2.3 EEG Signal Processing

The recordings of the EEG signals based on the abnormality or disorder contain individual patterns. This recording is very hard to capture the hidden pattern to identify the diagnosis. The major aim is to centre on the extraction of the global features and therefore it can recognize the single pattern which becomes limited. There are various signal processing approaches for recognizing EEG recordings to extract the features. However, there is a barrier among the non-seizure and seizure like the EEG signal. The EEG data signal processing forms a huge number of signal samples specifically the signal decomposition model is applied. This process needs the appropriate sample reduction to optimize the signal processing. The total EEG signals are split into more segments based on specific time intervals and then the representative sample from every segment in the whole signal data [10]. The stationary of signals is needed for the segmentation in the processing of the signal. The periodic pattern of the signal determines the period within the time casement.

The digital sample is based on the sum of all digital signals, which are always reacted by the noise formed in the analog signal which is the natural quantity based on the

experimentation also based on the compute during the ADC. Due to this purpose, it is difficult to refine the signal before another procedure starts. In this experiment, the EEG signal from every electrode is analysed based on multiple frequency bands by utilizing the bandpass filtering by forming six signals. By sampling the frequency, the upper limit is determined which is used in the signal acquisition related to the theorem of Nyquist–Shannon sampling. For signal processing, the frequency band utilized is related to the well-known human brain oscillation and they hide most of the available frequency spectrum [11]. The superposition of mode is the generic signal in the frequency domain. The square-integrable function $y(t)$ in S in general follows the relation that determines its Fourier transform in Eq. (1.1)

$$y(g) = \int_{-\infty}^{+\infty} y(t) f^{-k2\pi gt} et \tag{1.1}$$

At the same time, by make use of the Fourier transform, the signal $y(t)$ determined by the Eq. (1.2)

$$y(t) = \int_{-\infty}^{+\infty} y(g) f^{-k2\pi gt} eg \tag{1.2}$$

In python lab, the band-pass filter has been implemented with the environment by using the FFT technique. In general, a specific formula is used which is defined in Eq. (1.3)

$$Output = IFFT(passband * Fourier) \tag{1.3}$$

The FFT is represented by the Fourier of the input signal, The passband of the filter is defined by introducing the final output and the frequency domain in the IFFT of their product and indicates the filtered signal.

For the online model, the preprocessing steps were reduced. There is the down sampling in the raw EEG signals to 256Hz and cut in the 5 seconds of the overlapping segment. Subsequently, the signal time-frequency definition is commonly employed [12].It is believed that the process of the technique structure carefully takes into form how the visual interprets raw EEG signal time and the place may perform more explicit representation. The research mainly focuses on the EEG channel of ―F8-T8, T8-P8, F7-T7 and T7-P7‖ to form maximum recordings in the future utilizing the EEG wearable technique like the e-Glass. The preprocessing of the EEG signal involves some steps which are described in the following.

- Denoising and filtering: It removes the segments detected in the visual inspection. The digital filters are used in the temporal filtering mainly used to undertake the seizure prediction. By applying the linear phase filters, zero-phase filtering is performed. But also, the filters have better acceptance in the EEG signals. It helps to enhance the specificity and sensitivity of the prediction performance.
- Data segmentation: It helps to take out the preprocessed characteristic from the EEG signal and segment it into smaller windows. Based on the EEG analysis, the duration of the windows is varied. Hence the short window is related to compromising the ability to find the specific pattern. In the end, the long-term outperformed.
- Preictal time choice: Fixed preictal time is selected in some research and observed that there is no significant variation but it constantly reduces the FPR.
- Intervention time choice: Seizure prediction required a longer intervention time. It is recommended that the interesting findings be validated using the larger dataset. The 5 min of fixed intervention time attained promising result.

Each EEG signal segmentation approach is denoted in Figure 1.2. For every known seizure, we know the one-minute recording of interictal and the ictal recording. The time taken between the interictal and ictal classes is same as manage the quantity of sample training. To make the onset of a seizure, the interictal segment initiate two minutes and finished one minute earlier. Before the seizure onset, the immediate pre-ictal prior one minute is utilized for the training to support the correct classification between the ictal and interictal divisions. This follows the clinical expert's recommendation. The onset of seizure started by the ictal segmentation.

Some of the seizures can last for minimum time, higher the segment of ictal to involve some sudden post-ictal recording. Since the segmentation of the post-ictal is hard to discriminate from the ictal stage and has the chance to detect the seizure informative. From the immediate post-ictal, there is no need to attempt the separation activity based on the ictal recording of one minute [13]. The interictal management are denoted as the negative class segment based on the ictal segment known as the positive class segment. The training data are allowed by the balance with each file involving the negative sample and positive sample. The resolution is formed by the windowing strategy while predicting the seizure at the seizure level.

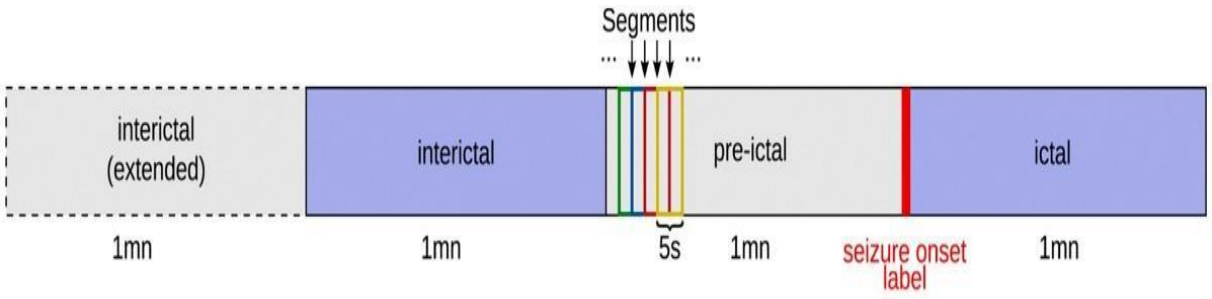

Figure 1.2: EEG signal segmentation

The approach to divide the data between the validation, testing, and training is demonstrated. Many of the information utilized for testing and training the level of segment based on the seizure level. This is defined by the testing and training sets A. This helps to function the splitting of 5-fold cross-estimation on the patients with every connection on the managing set to form the matrices at the level of segment and the variables were finely tuned for detecting the onset of seizure. This denoted the training and testing set B. The balance training set is consumed to identify and monitor the training performance in the early stopping. Without cross-validation, the training set A of the sample is used for validation.

The main intention is to pre-process the data to increase the signal of interest level. Also attenuating or rejecting the deleted signals in the recording marked by artifacts. Hence the artifacts were removed by the technique by applying three signals [14].

The section performed the pre-processing is applied in the Bern-Barcelona EEG dataset using the Butterworth filter. It reduces the unnecessary interference and noise begined in the seizure recognition. The EEG database which is the pre-processed sample signal is defined and the normal equation is defined in Eq. (1.4)

$$H^2(X) = |I(kx)|^2 = \frac{H_0^2}{1 + \left| \frac{kx}{jx_d} \right|^{2o}} \tag{1.4}$$

Here the order of the filter is denoted as o , cut of frequency is denoted as Xd . The EEG database is the noiseless dataset. Therefore, the information for the corresponding preprocessing and noiseless EEG data are consumed for processing.

1.2.4 Feature Extraction

Feature extraction is functioned to transfer the EEG signal to the rate that are used for the recognition. The loss of significant information is minimized by intending the extracted feature embedded in the signal. For the research, the feature of the frequency domain was extracted. Python was performed to make the script of the feature extraction. This file contains the digitized EEG signals with the edf-reader [15]. By using the wavelet, the signal processing technique avoided the deficiency and extra effective features in the time-frequency domain. In the basic function, the signal is denoted as a linear and non-linear combination. The features in the EEG seizure identification are determined by the following.

- Features of time domain
- Features of frequency domain
- Time-frequency domain features

The TDF is determined using the natural obtained EEG signals performed in the time domain. In EMD the signal transformation decomposes the signal into IMF and is commonly applicable for the signals that exit the non-stationary properties. Ictal and normal patterns discriminate by the group of statistical parameters.

For the reason, it is managed that EEG statistical distribution on the seizure and the normal period varies. The range of the data is quantified by the minimum and maximum values of the signal baseline. The frequency domain estimates are also a difficult process in which the frequency representation offers the information of the pattern in the EEG signal. The features are extracted by using the PSD and normalized PSD which indicates the power partition at every frequency.

The time-frequency domain occurred by correlating both the frequency and time domain. Also considered the several decomposition and transformation model that gives the information in term of time and frequency. The decomposition technique the result computed all the frequencies. The time-frequency distribution of the EEG signal represented by the statistical feature is in the following. Also, the illustration of the EEG electrode grid is defined in Figure 3.1.

- The maximum power of the wavelet calculation in each suband.
- The value of the whole mean measure of adjacent sub-bands.
- In every sub-band, the measures of mean absolute value are taken.
- The measures of the standard deviation in every sub-band.

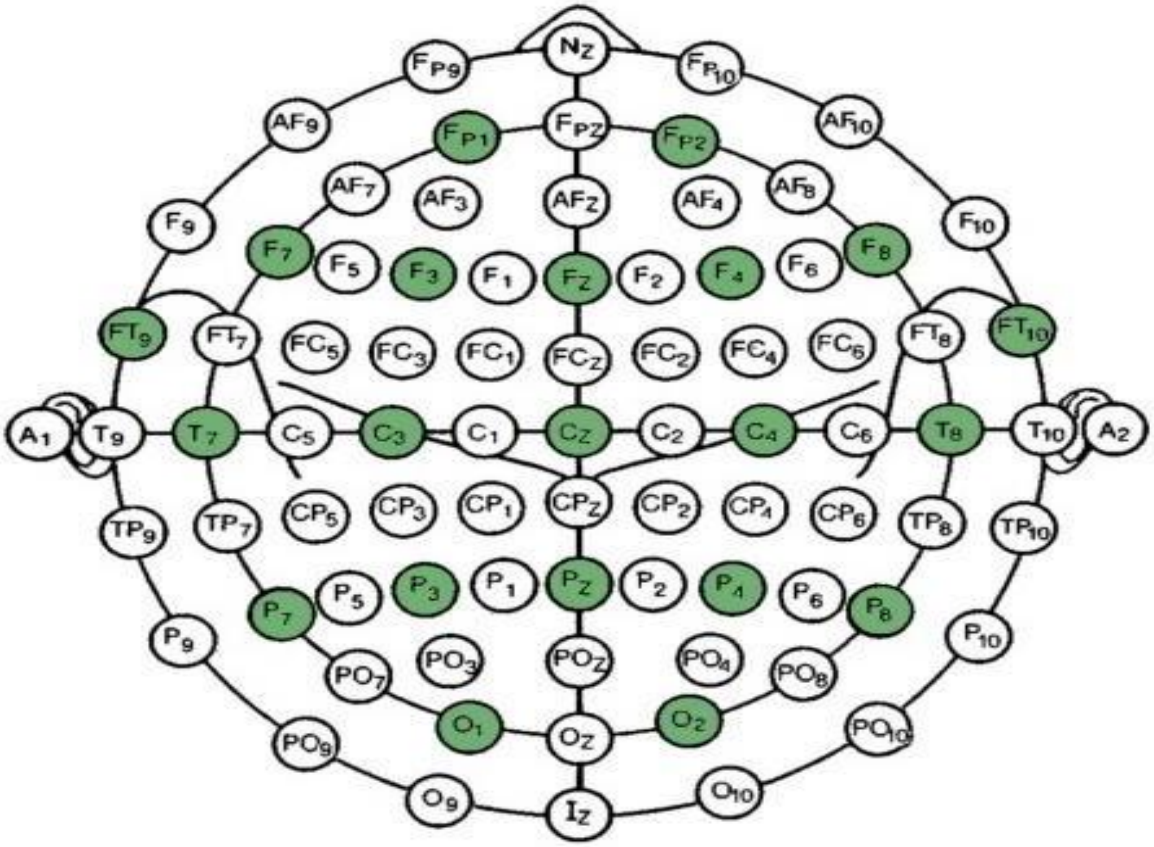

Figure 1.3: Diagrammatic view of EEG electrode grid configuration the used channel is shown in green

Feature extraction is designed to transfer the EEG signal to the values that are used for the classification. The loss of significant information is minimized by intending the extracted feature embedded in the signal. For the research, the feature of the frequency domain was extracted. In python was performed to make the script of the feature extraction. This file contains the digitized EEG signals with the edf-reader. EEG signals are generally categorized into individual well-known bandwidths for research and clinical studies. The majority of the seizure events are generally observed by the EEG bandwidth. Specifically, frequency domain analysis is reported in various research.

The EEG data contained in the file for the past hour, where the recordings are split into particular epochs to change the information more handleable and to split the data based on the activity type. The extract epoch is made by the function name which returns two cell arrays which involves matrices with the epochs obtained from the files of seizure and the non-seizure files. Figure 1.4 indicates the one-long hour of EEG findings from the channel involving the seizure. The time calculation of the seizure is more initiated and extracted as a seizure epoch.

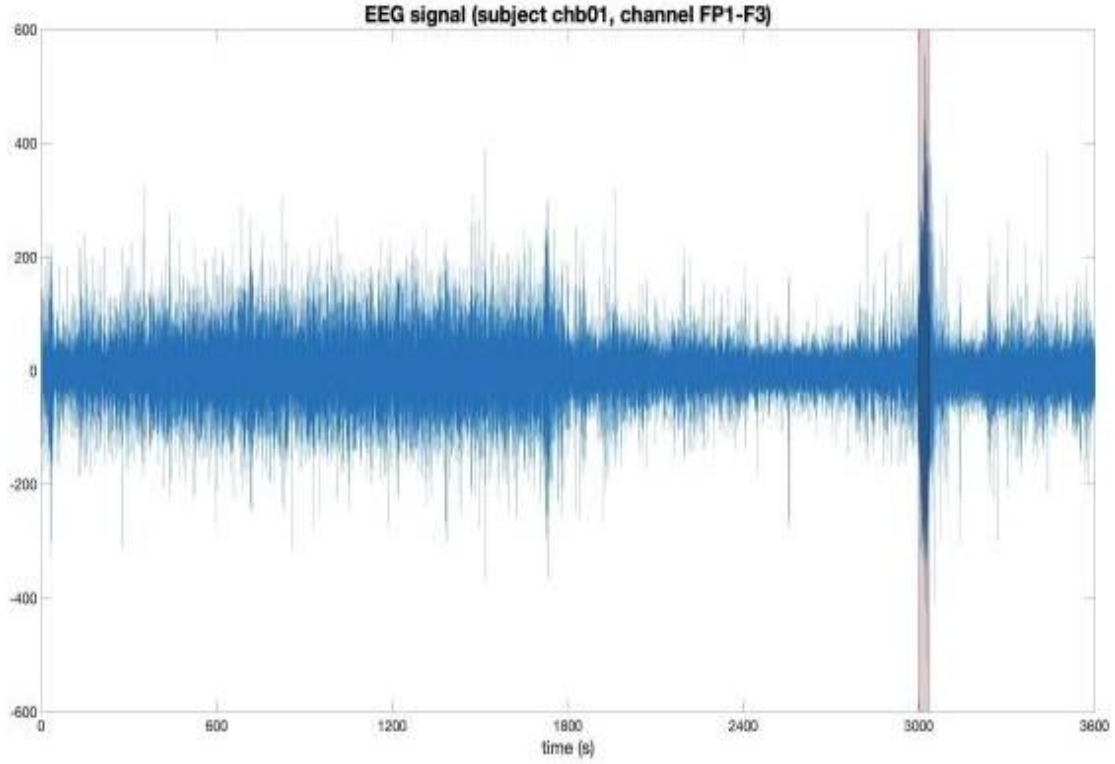

Figure 1.4: Visual representation of one hour EEG signal of the patient

After extracting the epoch, then created the feature vector. Based on the sampling frequency, data points performed per second are recorded. In the epoch window, the epochs are split into three segments. In the EEG data, the windows are set to the length nonstationary, which makes the necessary to extract the feature from a reasonably small time [16]. One second is set in the overlap length. To estimate the spectral densities power from each epoch window was utilized the transform the time signal sector to the domain of frequency. The measure of the power spectral density in which the content of signal power is the calculation of the frequency from the data. Image is representation of EEG Signal of the Seizure in Figure 1.5

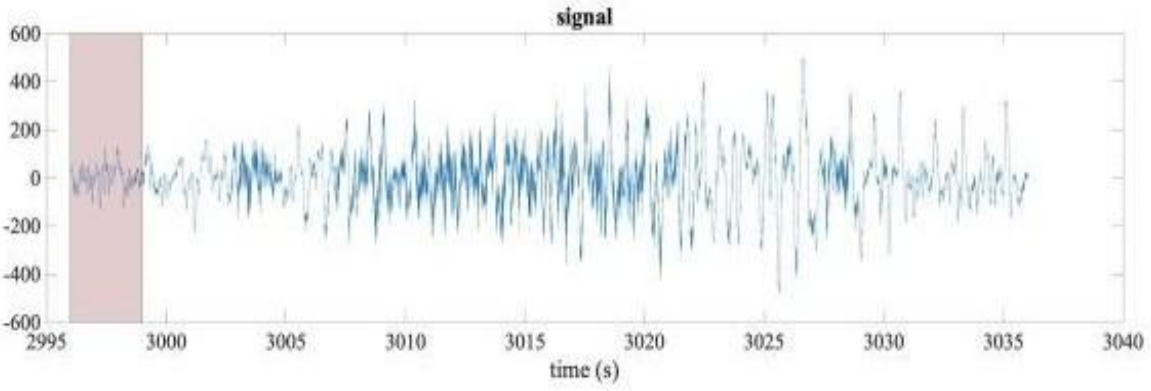

Figure 1.5**:** Image representation of EEG signal of the seizure.

With the whole extracted frequencies from the information data, spectral power in the frequency value for beta, gamma, theta, and delta were noticed. The function performed channel-wise and performed for total epoch window in the channel. Figure 1.6 defines the frequency component, that is selected for every window. Between all the channels, the average band power value is estimated element-wise, and the average feature vector fills all the feature matrices. The end matrix has the characteristic for the seizure data and the non-seizure data.

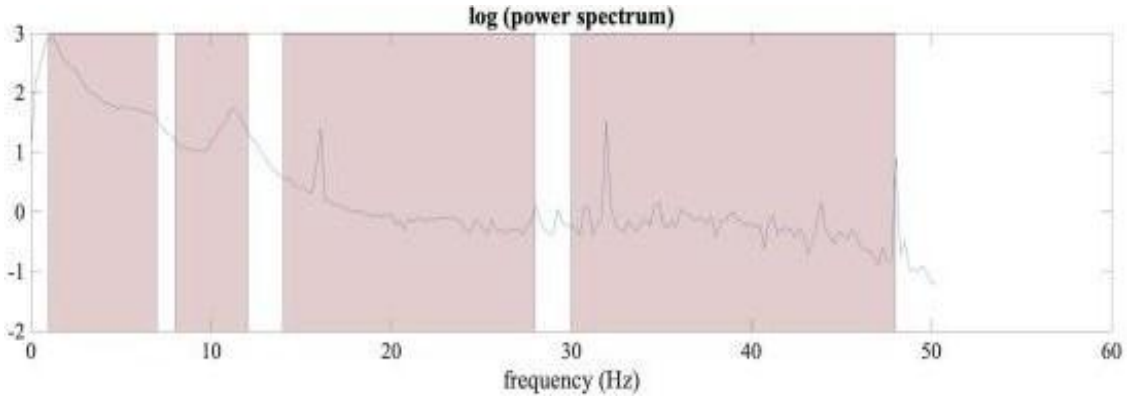

Figure 1.6: Extracted frequency interval from the signal

1.2.5 Classification using Machine Learning and Deep Learning Techniques

Multiple signal processing techniques are used to extract the necessary features for classifying the EEG signal recording. The algorithm used in the model is trained by the extracted features that construct the classification models. In this chapter, the classification of the approach is based on the following.

- Machine learning technique
- Deep learning technique

1.2.5. 1 Machine Learning Models

This sector in short outlined the machine learning approach used in the research to recognize the EEG data. The main aim of the techniques is to attain maximum accuracy and less latency in identifying seizures. The classical machine learning technique used for detecting epileptic seizures is the following.

- Support Vector Machine

- K-Nearest Neighbor
- Random Forest
- Artificial Neural Network

Support Vector Machine

One of the managed machine learning models is the SVM which constructs an optimization depends on the samples training that defines the further data classification. To identify the splitting hyperplane, it is the coolest form of the model, which splits the characteristic space into two classes. The input data are analysed as p vector dimensional and the dimension of hyperplane is $p-1$. This indicates the 2D data is divided by the 1D hyperplane.

Hence the line and 3D data are split by a 2D hyperplane in the plane. To evaluate the hyperplane of the margin optimally is analysed which is the reduced distance from the training observation to splitting the hyperplane. The margin maximized by separating the optimal hyperplane is defined in Figure 1.7. By assigning the data point, classification is done to the class that is related with the side of the point lying on the side of the hyperplane [17].

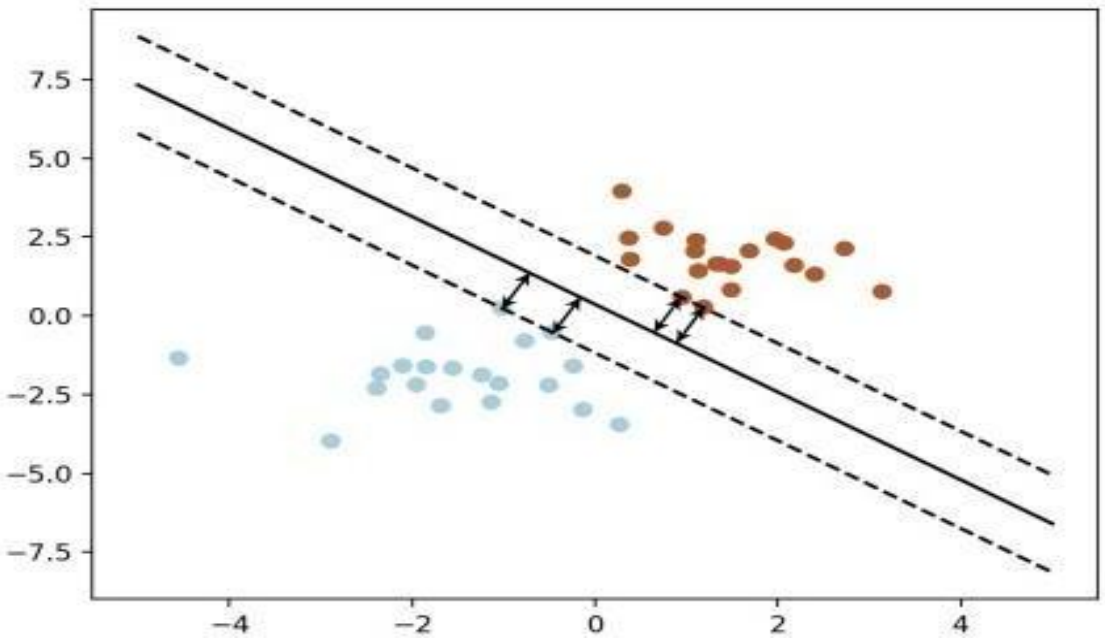

Figure 1.7: Graphical view of SVM for separating hyperplane

The location of points on the dashed lines is called the support vector and they are decided completely by the boundary between two classes. The decision boundary is moved by the removal of the data point. The boundary remains the same when the other data point is removed which is not located on the margin. For more complex classification, the SVM performs well and the data become non-linearly separable. To this extent, the hyperplane separation is highlighted by utilizing the kernels. Various kernels are used to manage multiple value of decision boundaries and most general contain a radial kernel or polynomial kernel.

K-Nearest Neighbour

Another approach consumed in the experiment is the K-Nearest neighbour, which takes a correct integer of fixed K and recognize the new data point by knowing the first K point in the training set. The probability of the conditional class $k(k = 0,1)$ is estimated as the fraction of the point labelled with the class k. Finally, the Bays rule is utilized to manage the $y0$ with the largest chances. Figure 1.8 defines a normal standard of how the data are separated depend on their value K. Based on the choice K, the KNN classifier and the related decision boundary changes exceedingly.

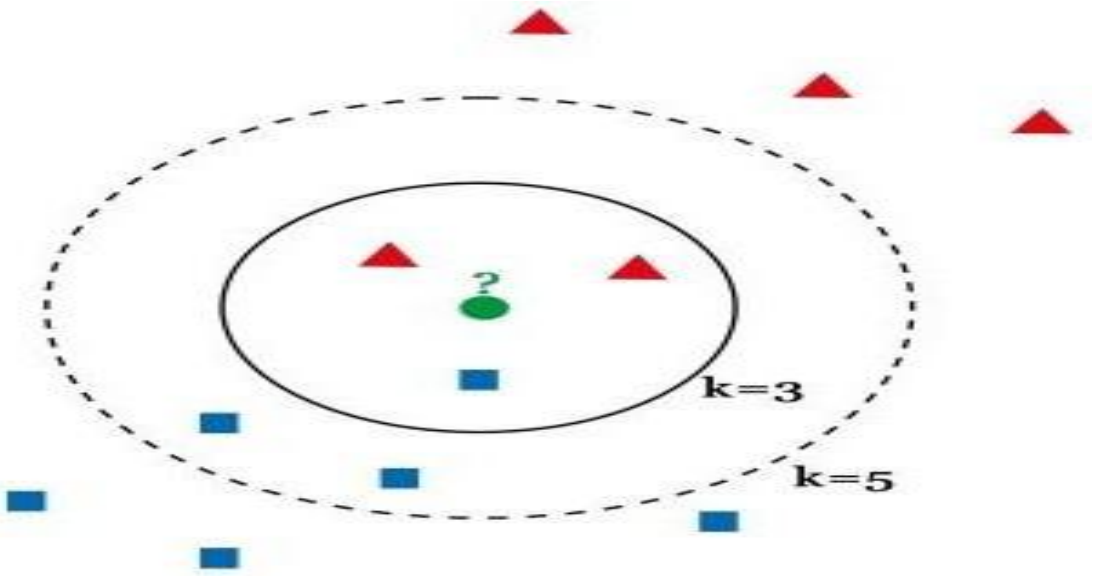

Figure 1.8: Illustration of KNN based sample classification

The range K involves how adaptable the boundary is and thus the bias and the variance. The minimum range of the $K(K = 1)$ cases is a most adaptable boundary with minimum bias and large variance. At the same time, the rate K improves nearly linear boundary decision. The best way to select the K is to analyse the square root of the whole

value of data points. When handling the two data, an odd value K was chosen to stop difficulties between the classes.

Random Forest

It is the categorization method, that is generally based on the random tree. In this technique, each input feature is compared to the training dataset to know the best solution. In most of the popular classes, the recognition accuracy is maximum. The attributes are randomly selected by the decision tree at every node [18]. The major steps used in the random forest are derived in the following.

- The training set is formed by selecting the random value, which replaces the original data.
- For each tree random number of attributes are selected. Here the nodes are formed by the attributes using the standard algorithm.
- By using the input vector, the object is classified and the class is selected based on majority.

Artificial Neural Network

ANN is performed by comprising the weights and neurons. The input value passes through the function with the help of neurons output the results and the weight carries the value between the neurons. This neuron is classified as input, hidden, and output layer. The multiple input units present in the represented input layer for the information to be subjected into the network. The hidden units in the hidden layer depend on the activity of the input unit and the found connection weight between the units of input and hidden layer.

1.2.5.2 Deep Learning Models

The section describes EEG-based epileptic seizure recognition depends on a deep learning technique. The epileptic seizure identification by utilizing deep learning is presented in the following.

- Convolutional neural network
- Recurrent neural network
- Deep belief networks
- Convolutional recurrent neural networks
- Convolutional autoencoders

Convolutional Neural Network

CNN is one of the famous deep-learning networks. At first, they were used for image processing applications but then started the one-dimensional and two-dimensional structures for the prediction and recognition of disease depends on biological signals. This class is mostly utilized for the finding of epileptic seizures using EEG signals. In 2DCNN the EEG signal is transferred to the 2D plot by introducing the spectrogram model and then applied to the input convolution network. In the 1D CNN, the input is sent to the 1D part and the signal for detection purposes [19]. Hence both the 2D and 1D can perform and process the EEG signal for seizure detection.

Recurrent Neural Network

The sequential data shows features like variables, which causes them not acceptable for the normal deep learning model. A significant part of this data information required the deep learning scheme to process the data. RNNs are mainly used for analysing the solution for physiological signals. The functional RNN used for epileptic seizure identification is shown in Figure 1.9.

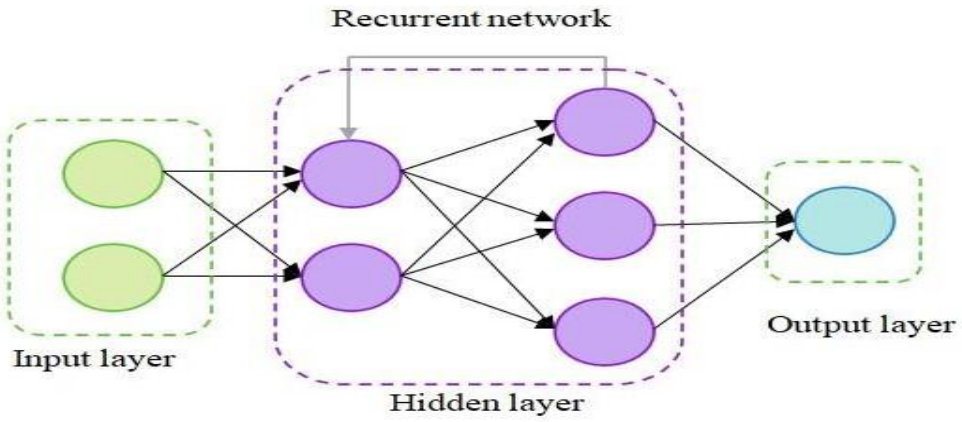

Figure 1.9: Architecture of RNN model that can be used for seizure detection.

LSTM: It is mainly used to reduce the short-term memory issues. The gates in the LSTM are used to regulate the flow of information. The long sequence in the data is prevented by the gates. The LSTM is formed by the construction of gates and cell state. The combined layer with the LSTM structure was obtained to form a better outcome. In the fully connected layer, sigmoid activity is used for recognition purposes. The LSTM and GRU model is employed with the activator and one layer of the fully connected layer.

GRU: It correlates the input and forgets gate into the update gate. Here the gating signal was minimized to reset gate and updating gate. These gates finalize the information

to pass through the output gate. The input signals divide into time and spectrogram in the proposed model during the preprocessing stage. Then it is further passed to a four-layer for accurate classification.

Autoencoder: It is the unsupervised model in which the input is the same as the output. The input is combined with the latent space indication and the output is formed from the representation. Hence in an autoencoder, the performance are coupled with a neural network. Auto encoders are widely used in feature extraction on the processing of brain signals. The autoencoder used for epileptic seizure recognition is defined in Figure 1.10

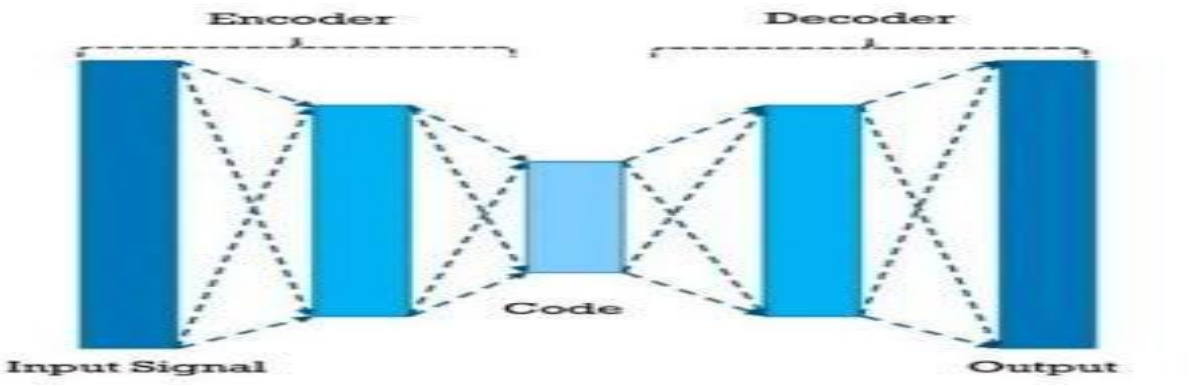

Figure 1.10: Illustration of AE network that may be used for seizure detection.

In the scheme, the feature is extracted from the input EEG signal using the autoencoder. The classification of the approach is performed by the SVM model. The signals first passed in the deep network segment in the preprocessing stage. This provides more accuracy in the classification phase.

Deep Belief Networks

DBN: It is formed by stacking the RBM in the block of the DBN. Itis the hybrid unsupervised generative deep learning formed by the stochastic and latent functions in multiple layers [20]. The DBN variation is the convolutional DBN, which analyses the high-dimensional model used for the spatial information. DBN is the unsupervised, probabilistic, and generative deep learning model which has a hidden unit with multiple layers. DBN is utilized to detect the epileptic spikes in EEG data. The three hidden layers in the developed structure achieved the accuracy of the model.

Convolutional Recurrent Neural Networks

The most effective implementation in deep learning networks is to forecast and detect epileptic seizures from EEG signals in CNN-RNN structure. The basic RNN is added to the convolution layer to find spatial patterns based on the time-series data. The modified CNN-LSTM structure was developed by comprising the 13 layers which demonstrate the better performance of the model.

Convolutional Autoencoders

In the autoencoder framework, parameters in the model are reduced by the convolution layer. The combination of this model makes the unsupervised feature extraction for the identifying of epileptic seizures. The 2D-CNN and the autoencoder are utilized to extract the supervised and unsupervised features from the data. The input signal directly formed the unsupervised feature from the spectrogram of the signal. For the classification, the SoftMax classifier is used for accurate detection.

1.3 Research Motivation

From the research, the selection of channels for feature extraction is one of the major issues. Various approaches are utilized to select the EEG channels and the methods use all available channel data based on the data and entropy to done the selection. The selection of more channels causes computational and overfitting costs. Here the researchers focus on cross-patient classifiers to use the electrodes equally distributed on the scalp. The other potential issue is the artifacts from their recording of EEG cause deletion. This will affect the resulting outcome. The anticraft are used to measure the brain signals, but it has the probability of being in accurate because many of the signal do not originate from the brain. The technique of seizure detection is devised that uses the EEG signal for identifying the epileptic seizure. Here the major issue confronted for identifying seizures is to discover the related demonstration of EEG to distinguish epileptic and non-epileptic scenarios. In many of the applications machine learning is applied to medicine in the data presented for training the classifiers. It is difficult to find the type of seizure among the large number of patients. The classifiers are used to generate promising results for the tested dataset.

1.4 Research Objectives

The major objective of the thesis is to improve the recognition technique to analyze epileptic seizures based on the EEG signal. It also incorporates preprocessing, feature extraction, and classification to find the effective detection approach. The sub-objectives of the thesis are defined in the following.

- To present the effective model for the epileptic seizure identification with the help of EEg signals. It also includes the preprocessing, feature extraction stages to improve the performance.
- To implement the EEG signal preprocessing step for the efficient classification and also to remove the unwanted noise in the seizure identification.
- To introduce the feature extraction procedure by selecting significant features based on the developed model to minimize the feature length and evaluate the classification performance.
- To present the new heuristic algorithm to enhance the feature selection and identification process by tuning the parameters correspondingly.
- To ensure the function of the developed epileptic seizure classification model by comparing it with other traditional approaches shows the improvement of the developed model.

1.5 Contributions of the thesis

The necessary contributions of the provided thesis are listed in the following.

- The suggested model developed the novel epileptic seizure identification by utilizing the I-ELM. Initially, EEG signal data are collected from the publicly available dataset and sent to the pre-processing stage. Here the STFT and DWT performed the preprocessing and signal decomposition. By using the spatial and temporal extraction model, the signal decomposed, and feature extraction happened. The new heuristic model called M-TSA is used to minimize the feature-length for handling the difficulty in the training and improve the detection performance. The I-ELM model adopted techniques like DNN, Fuzzy, and LSTM. The proposed I-ELM is improved by using the developed M-TSA for detecting the seizure.

- The novel seizure identification using the EEG signal is used for feature extraction and classification processes. Preprocessing is the starting phase of the model. The DWT and EMD models combined to perform the signal decomposition process. By concatenating the LDA and PCA the feature selection processes happened. The weight is optimized by the J-CSO in the feature selection approach. The heuristic algorithm does not need any specific parameter to improve the model. The functionality of the proposed model is more advantageous than the conventional models. The detection is performed by the J-CSO-based I-ELM model.

1.6 Organization of the Thesis

The establishment of the thesis is demonstrated below.

- Chapter 1 granted the epileptic seizures, its selection, processing, pre-processing, feature extraction, and its classifications. Subsequently, it determines the research motivation and contribution of the thesis.
- Chapter 2 demonstrates the various types of research introduced for epileptic seizures detection and is accompanied by the research gaps and complexities.
- Chapter 3 improved ensemble learning model for the automatic detection of epileptic seizures framework with optimal feature selection
- Chapter 4: illustrates the development of hybrid heuristic weighted feature selection and ensemble learning for an epileptic seizure detection framework.
- Chapter 5. illustrate the Comparative Analysis studies
- Chapter 6 , this thesis's conclusion and future tasks are calculated in the end.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Epilepsy is a general disease that troubles all age groups. It is a ―chronic neurological‖ disease in that continuous seizures happen because of the unusual neural performance in the internal brain of humans that troubles the movement and mood of the sensorium of the human body. Enormous enhancement of the patients urges the demand for automated seizure identification approaches for EEG information. The EEG generally identifies seizure performance as it influences the electrophysiological situations of the brain during the offered period and is largely employed for detection because of its low price. The EEG signals improved with the pathological and physiological information utilized to estimate and decide the treatment and the epileptic patient's progress. Generally, the experts estimate the EEG signals for some activities. The automated identification of an epileptic EEG model is a difficult approach due to the non-stationary and non-linear attributes of the EEG. EEG is a standard mechanism to identify the overall seizure types in the medical sector, but no effective wearable EEG is available till now to change this mechanism for everlasting observation at home. With the enhancement of deep learning in the bio-medical sector, some of the approaches have been implemented to predict and detect seizure occurrences from the epileptic patient's EEG, primarily stored during the observation with the powerful EEG. Although some of the techniques defined the exemplary functionalities, others employed offline estimation with important transformations, and the EEG signal's pre-processing task was not adaptable to the low-power, long-term, and offline tasks. The seizure pattern information of the EEG is a highly different kind that can vary greatly across patients and also takes more time for a similar patient. Because of these troubles, some of the works are being constructed to implement an automated seizure identification mechanism. The primary concept of these approaches is ―feature extraction‖ to detect different kinds of seizures with a high accuracy rate. However, the time domain attributes are vulnerable to slight variations in the seizure activity because of the non-stationary signal information of the EEG, and their statistical attributes are different across diverse subjects and across diverse times for similar subjects. Therefore, a thorough investigation is required to detect a new automated detection approach for seizure activities.

2.2 Categorization and Description of Works

- Deep learning-based epileptic seizure identification
- Machine learning-based epileptic seizure identification
- Wavelet transform-based epileptic seizure identification
- Fuzzy-based epileptic seizure identification
- Optimization algorithm-based epileptic seizure identification
- Miscellaneous-based epileptic seizure identification

2.2.1 Deep learning-based epileptic seizure detection

In 2022, Gutierrez *et al.* [21] have developed an ADLBSC-ESD mechanism to overcome the problems presented in the traditional brain signal categorization approaches. The recommended task concentrated on categorizing the signals of brain to estimate the presence of seizures or not. Moreover, the recommended task included the implementation of the ITCBO mechanism for choosing the attributes from the EEG signals. In addition, the DBN task was employed for an effective EEG signals categorization and the attributes of the DBN network were optimized by adopting the AAS. To confirm the enhanced brain signal categorization functionality of the implemented system, a set of simulations were carried out and the solutions were examined in terms of various metrics. The research values demonstrated the better functionality of the recommended task over the present stage of the conventional tasks with the highest accuracy.

In 2024, Anita and Kowshalya [23] have concentrated on implementing an improved deep-learning framework with the EEG signal for conducting the automatic identification of the epileptic seizure. Firstly, the EEG signal was accumulated from advanced sources and the FBSE-EWT approach was employed to perform the signal decomposition from the garnered information. After that, the feature extraction was conducted, where the decomposed signals were employed. This operation also utilized the autoencoder. To decrease the computational burden, the "relief-F feature making" approach was adopted for selecting the necessary signal attributes. The MSA-DCNN and the LSTM were adopted that is called HDS to recognize the seizures with the very essential attributes for the categorization of the seizure. After that, the SMO and the BWO were composed to create the ASMBWO that was utilized to conduct the parameter optimization into the categorization mechanism. Utilizing diverse metrics, the numerical

estimation was conducted among the traditional detection mechanisms of epileptic seizure and the recommended task to provide an improved functionality of the implemented approach.

In 2023, Qiu *et al.* [28] have suggested a DARL Net that employed a LSTM and Resnet to attain the temporal dependencies and the spatial correlations. In addition, a special layer was implemented to mine extra data for the epileptic seizure. In addition, the channel attention sector was presented to create the system to concentrate the seizure-related data. Some experiment sets are presented to estimate the functionality of the DARLNet according to the given data source that estimated the supremacy of the work on the epileptic seizure identification mechanisms.

In 2023, Zaid *et al.* [29] have recommended a combined, pre-processed, and modified EEG signals as input to diverse deep-learning tasks for the classification of epilepsy seizures. Numerous integrated and pre-processed EEG signals have been estimated with three distinct deep learning frameworks such as DNN, averagely complex 1D CNN, and finally complex 1D CNN. Experts conducted some of the estimations for the three and two-class epileptic seizure categorization on the given data source utilizing the suggested EEG signals like raw EEG signals integrated with squared EEG signals, standardized EEG signals, and source EEG signals presented in the dataset, etc. Extensive comparisons and estimations displayed that the best outcomes were attained on the entire deep learning frameworks with lower computational attributes.

In 2023, Jibon *et al.* [32] have presented a hybrid task for the identification of epileptic seizures by employing the DenseNet and LGCN. When contrasted to the conventional deep learning frameworks, the DenseNet attained memory efficacy and more computational accuracy by minimizing the issue of vanishing gradients and strengthening the propagation of attributes in all the layers. The ―S-transform‖ was adopted to pre-process the source EEG signal and further compose the resultant matrix into frequency sections for the LGCN inputs to utilize for the election of features and then the DenseNet was employed for the categorization. The recommended work performed better than the traditional approaches in the extensive analysis of the online sources.

In 2023, Britto *et al.* [33] have offered the hybrid CNN-Bi LSTM network to solve the issue of recognizing the epileptic seizures from the EEG evaluation. The model included three modules like pre-processing, extraction of features by employing the multi-dimensional CNN, processing of temporal features by utilizing Bi-LSTM, and categorization utilizing the FC layers. The initial phase included the normalization and the

pre-processing of the original EEG signal for the further validation. This phase was supported by standardizing the input and preventing the noise for the further execution. After that, a multi-dimensional CNN was suggested to efficiently draw out the attributes from the pre-processed EEG information. The CNNs were popular for their capacity to attain the spatial attributes and in this stage, the CNNs were employed to draw out the related attributes from the EEG information. After performed the ―feature extraction‖ phase, the Bi-LSTM was employed to execute the extracted attributes and obtain the temporal dependencies. The network called Bi-LSTM was very effective for the linear modelling approaches and could capture the everlasting dependencies effectively in the information. By employing the Bi-LSTM, the framework concentrated on identifying the seizures and categorizing them into certain kinds utilizing a ten-class categorization mechanism. The recommended work provided large identification accuracy and the outcomes recommended that the method performed accurately on recognizing the epileptic seizures with the assistance of EEG signals. In addition, the recommended work illustrated the superior functionality contrasted to other classical tasks like KNN, DT, and SVM concerning accuracy. It is essential to consider that the comparison and the evaluation of the designed work were conducted on the online data sources. Finally, the suggested hybrid mechanism displayed powerful outcomes in the categorization and identification of the epileptic seizures by EEG signals and highly enhanced the precision and efficacy of the treatment and diagnosis in the starting phases of these diseases.

In 2023, Shoka *et al.* [36] have presented an effective and new encrypted EEG data categorization and identification method utilizing the "Chaotic Baker Map and Arnold Transform" tasks with CNN. In this model, the time series of EEG channels were initially changed into a ―2D spectrogram‖ picture and further encrypted utilizing the "Chaotic Baker Map and Arnold Transform" mechanisms and at last subjected to the CNN-aided TL mechanisms. From the estimation outcomes, the recommended task was estimated and validated on the public source and attained better performance by the Google net than the other approaches such as Resnet 50.

In 2023, Zhao *et al.* [38] have utilized the transformer and CNN methods for a seizure identification approach according to the interactive global and local attribute coupling. The global and local attribute indication of the EEG was drawn out by the self-attention and the convolution tasks. In order to prevent the problems in the indication of global and local attributes, an FCB was adopted to integrate the 2 categories of data in a communal direction. The improved attribute indication was subjected to the technique for

the normal and seizure EEG categorization. The numerical research was performed on the data sources. The experimental outcomes illustrated that the approach could efficiently do the seizure identification from the source EEG signals with the absence of any special extraction of the feature.

In 2022, Gao *et al.* [41] have provided a normal sample-weighted approach for the patient-specific estimation of epileptic seizure. Most importantly, experts explained the linking from the model weights of learning groups to the functionality of the evaluation groups at the objective measure to be tuned. Further, the ―genetic algorithm‖ was utilized to tune this fitness measure and attain the best model weights. In the end, experts attained the final approach by employing the learning sent with the tuned sample weights. In order to estimate the efficacy of the presented work, experts performed extensive research on both classical machine learning tasks and the present deep learning tasks. Expert mechanisms could highly enhance the functionality according to these approaches. Among them, the expert's mechanism according to the transformer attained a better outcome concerning various metrics from the standard source. This experiment ensured that the advancements in the medical sector by taking the EEG samples. In addition, experts presented a normal network that utilized the overall conventional categorization approaches and could enhance the functionality according to these approaches.

. In 2021, Chakrabarti *et al.* [48] have offered an LSTM task that was not complex and had the ability to identify the epileptic seizures efficiently from the invasive and non-invasive EEG records. The suggested work was effective and simple. Also, the approach that utilized the original EEG signals could be employed to identify the seizures. Moreover, a generalized mechanism was utilized that was channel-based so that the EEG signals owned to any brain hemisphere could be troubled by the recommended framework. The identification approach of seizure attained mode sensitivity and less FPR rate for the standard data source. Convergence estimation of the recommended work offered an important amount of correctness and reliability in the effective identification of the seizures. The experiment of the suggested work on invasive and the non-intrusive EEG signals displayed that the presented approach performed better for diverse kinds of EEG records as diverse factors presented acceptable outcomes. As the mechanism was simple and didn't demand any extra attributes optimization approaches, it minimized the execution overheads without any influence on the accuracy. Therefore, it could be employed as an effective approach for observing the epileptic seizures.

In 2022, Beeraka *et al.* [60] have concentrated on improving the epilepsy seizure identification utilizing the deep learning approaches with the development of the STFT section. Identification of the seizure had been attained in the upcoming phases such as time-frequency estimation of the EEG segments utilizing the STFT, frequency bands extraction and the attributes of interest, and the identification of the seizure utilizing the Bi-LSTM and CNN. For this task, the "Bonn EEG" data source was adapted. The highest error of approximately 0.13 % was obtained while the STFT result produced a comparison via the suggested hardware framework vs. the solution created through the simulation was performed. The better mean categorization accuracy was obtained by the Bi-LSTM and CNN taking the overall frequency bands for the non-epileptic and epileptic patients.

In 2023, Poorani and Balasubramanie [61] have presented two distinct deep learning approaches for the patient-dependent seizure identification utilizing the effective data and it offered better outcomes than the conventional deep learning approaches. The initial approach concentrated on the 1D CNN and the next approach focussed on the hybrid frameworks of LSTM and CNN. In the end, it was ensured that these two mechanisms offered diverse functionality for diverse patients.

In 2022, Singh Malhotra [62] have suggested a cloud-fog combined intelligent neurocare mechanism that conducted a temporal estimation of the original EEG signals employing the deep learning to recognize the existence of epileptic seizures. The patient-independent mechanism utilized the separate-channel EEG signals to attain the present period and computationally effective seizure identification at the system's layer of fog. It utilized a high variance-aided selection of channel strategy to choose separate channel of the original EEG signals accompanied by the segmentation and filtering into multiple short-time temporal segments. To evaluate the patterns of EEG, these segments were then given to the suggested approaches of SAE, RNN, and CNN classifiers. The functionality evaluation via simulation outcomes effectively expressed that the suggested CNN-aided temporal evaluation mechanism provided better functionality than the other tasks. Hence, the recommended CNN-aided task emerged as an important task for the precise and rapid recognition of the seizures in the environment of an integrated fog-cloud.

.In 2021, Thara *et al.* [74] have discovered a task according to the SB-LSTM with the GAP network for identifying the events of epileptic seizures. Experts employed the online EEG data source and the task was estimated according to the three functionality factors accuracy, sensitivity, and specificity. It provided the better functionality in identifying epileptic seizure activities that were the largest accuracy between the overall

approaches presented in the traditional works. The other merit of the presented work was its robustness in the sound. In the present time, the EEG secured in the medical labs included artifacts constructed from the muscle and the eye blink events of the sick persons. When the expert approach was utilized by the clinicians the EEG data including artefacts subjected as input to the approach for identifying the seizure activities. Thus, experts were required to implement an approach that was robust over noise and that could offer better outcomes even in the EEG records including the artifacts fed as input. Thus, experts enhanced the validation to measure the functionality of the presented work by including the muscle and eye blink artifacts in the given EEG records. The approach was capable of providing better outcomes even after including the artifacts. Hence, the suggested task provided the superior outcomes for the EEG without and with the noise contrasted to other traditional mechanisms.

In 2022, Cleatus and Thungamani [77] have recommended a computer-assisted approach to identify the ictal and the pre-ictal events from the multichannel EEG signal. 3 pre-processing approaches were employed to the EEG time-region signals to create an image data source were recommended here. This data source was subjected to the machine learning tasks for the categorization. Transformation of the period region EEG signal to a picture was achieved by drawing out the EEG signal attributes like mutual data, STFT, and the correlation coefficient. The executed EEG waveform that was denoted as images was employed to train the CNN. The CNN categorized the input signals into 3 classes such as pre-ictal, normal, and the seizure. Experts employed the transfer learning approach that employed the ―Alexnet‖, a previously learnt CNN framework for the image categorization and the training. Then, the learning about the correlation coefficient, mutual data, and the spectrogram image indications of the EEG signals, experts attained high validation correctness.

In 2022, Ravi *et al.* [80] have detected the epilepsy with the support of the EEG that estimated the brain's electrical activity that was regarded as the dynamical model. The neural networks of epileptic were constructed of critical non-sequential frameworks whose non-sequential character distinct in the EEG signals. Because of the non-linear and the chaotic character of the EEG signal experts suggested the utilization of the RP to obtain the non-sequential EEG sector. The underlying feature of the dynamical models is recurrence and included the data about the model feature. The RP was a component for the visualization and the evaluation of the varying model's functionality. The ―ensemble ResNet‖ learned on these RP attained more accuracy in various class imbalance

situations.

Similarly, the specificity and the sensitivity were also attained higher values in the class integration situations. Such an approach could help in the detection of the disorder and could provide an early notification to the sick person on the seizure onset.

In 2020, Yu *et al.* [88] suggested a CNN and LMD for the prediction of seizures. Initially, the LMD was suggested to decompose the original signals into the PFs strings. Moreover, three PFs were chosen to understand the EEG attributes utilizing the CNN. To attain the very significant data from the attributes drawn out by the CNN, the PCA was performed to prevent the redundant attributes. Then, the attributes were subjected to the "Bayesian linear discriminant" evaluation for categorizing the cerebral stage as preictal and the interictal. The recommended task attained high sensitivity with less prediction rate utilizing the given data sources. The research outcomes recommended that the implemented approach could become a power mechanism for forecasting the seizures in the medical development.

2.2.2 Machine learning-based epileptic seizure detection

In 2023, Kaur and Gandhi [25] implemented a task according to the image representations of the EEG, and for the identification of the seizure, they used for learning. In the beginning, the pre-trained approach was finely tuned to the representations of EEG, and hence the attributes were drawn from the learned approach by conducting the activations on diverse network modules. Moreover, attributes were given to the SVM for the classification utilizing a 10-fold information-dividing approach. The recommended task provided a high level of categorization functionality for both the clinical and standard data sources that was more effective than the traditional approaches. The high enhancement in the deep learning sector had generated a platform shift in epilepsy detection. The recommended task highly offered the related EEG segments for the specialists to analyze and enhance, minimizing the time complexity in the long-period scanning of EEG images.

In 2024, Sanchez *et al.* [31] have offered a mechanism with the support of KNN, homogeneity index, and wavelet packet transform to forecast epileptic activity before processing the ECG signals. The efficacy of the presented work for forecasting the seizure is estimated by utilizing a data source offered by the MIT-BTH that included some patients with epileptic seizures. The outcomes showed that the suggested work forecasted the epileptic seizure effectively and with more accuracy.

In 2023, Abbas *et al.* [34] suggested and validated a patient-independent seizure identification mechanism that employed the stable EEG-aided attributes attained by contrasting various feature selection mechanisms. The approach was partitioned into five sections, such as graph centrality, statistical, sparse learning, information-theoretic, and similarity feature selection approaches. The feature stability of these mechanisms was estimated by the RF categorization utilizing similarity, correlation, frequency, and intersection metrics. Evaluations with standard data sources were very effective, with a high categorization rate.

In 2023, Babu *et al.* [37] concentrated on enhancing the H-CFCA, which was a feature categorization mechanism utilizing deep learning and machine learning tasks for recognizing epileptic seizures and autism with the EEG information. This included a linear composition of the functional sections that contained CFCA, extraction of features, dimensionality reduction, and EEG pre-processing. The approach included db4 WD for performing the pre-processing of EEG into five diverse frequency bands, accompanied by the DVM for the reduction of dimensionality. After that, the H-ICA was subjected to drawing out the ICs. These ICs are further given to the H-CFCA, including SVM, and accompanied by the BiS-LSTM to recognize the existence of seizures and autism. The estimation of the recommended approach attained high performance rates. This work found that the approach was feasible and effective with the capacity to manage large EEG sources, accomplished less computational burden, and also enhanced the categorization of the feature. The numerical estimation displayed that the H-CFCA attained more sensitivity and accuracy compared to the traditional ―deep learning and machine learning‖ -based mechanism. The feature categorization approach of the EEG highly advanced the diagnostic accuracy, enhanced social well-being, and attained technological innovation in the medical sector by improving the categorization mechanisms and data estimation methods.

In 2022, Zhang *et al.* [56] combined the statistical and signal decomposition mechanisms to realize the categorization and identification of epileptic seizures. Initially, the VMD approach was employed to draw out the factors of IMFs by performing the EEG signal decomposition. Further, a statistical approach was adopted to estimate the eight attributes such as volatility index, varied coefficients, kurtosis, skewness, variance, average, minimum, and maximum for the energy-extracted IMF factor. In the end, the best interactions of the extracted attributes were given to the NLTWSVM to categorize the signals of epilepsy. The data source for EEG was obtained from the standard source and

employed to examine the efficacy of the designed approach for the recognition of seizures. The last research outcomes illustrated that the categorization accuracy of the suggested approach was high, and the outcomes revealed that this task had the potential to support clinicians in categorizing the kinds of epileptic seizures in the medical sector.

In 2020, Savadkoohi *et al.* [58] investigated the features of the brain's electrical functions from diverse physiological cases and the recording locations for the identification of the seizure. The clinicians found the task supportive in the accurate and timely identification of the epileptic seizures of their sick patients. Experts discovered the optimal path to identify the significant patterns from the EEG epileptic. The signals employed in this work were from diverse, healthy volunteers. The attribute engineering was conducted utilizing the SFFS, attribute selection with the T-experiment, FT, and WT correspondingly, time-domine frequency regions through the "Butterworth filter", and the extraction of features for every EEG wave in the period. The KNN and SVM approaches were conducted to categorize the pre-processed EEG signal. The functionality evaluation was conducted according to multiple performance metrics.

In 2022, Pattnaik *et al.* [69] employed the WT to identify the epileptic seizures on the EEG signals and categorized them with the machine learning mechanisms for the events of non-seizure and seizure. The stored EEG signals were gathered by the online resources, and overall, 48 cases were taken for evaluation. The EEG signal was partitioned into distinct ―sub-bands‖ utilizing the TQWT, and time-frequency-aided attributes such as temporal and entropy measures were drawn out to create a high data source to identify the epilepsy cases precisely. The information source was then executed for the categorization of epilepsy, utilizing the RF and SVM approaches. It was observed that the RF task attained better categorization functionality in terms of sensitivity and accuracy than the AVM classifier. Therefore, the recommended approach-aided RF and TQWT were the best options for the precise identification of epilepsy in the medical sector.

In 2023, Goel *et al.* [76] deployed a non-conventional approach in that the time series signals of the EEG were changed into various recurrence sections. The transfer learning approaches were employed to draw out the attributes from these recurrence sections, and the related attributes were chosen by employing the PCA, thereby minimizing the computational burden. These attributes were given to multiple machine-learning mechanisms that contained SVM, bagging, RF, Gaussian, KNN, and DF. Among these mechanisms, the SVM provided the best functionality. This was ensured to be a mechanism as it estimated the functionality of diverse machine learning in diverse paths.

Initially, with the drawn-out attributes only, and next, by employing attribute selection on the extricated attributes. The solutions ensured that utilizing attribute selection improved the functionality of every mechanism, hence estimating the efficacy of feature extraction utilizing deep learning. The recommended task has the power to categorize ―non-epileptic and epileptic EEG signals‖ very effectively concerning the balance between accuracy and sensitivity. This was a joint merit as it employed a hybrid and non-conventional mechanism to categorize the original EEG signal, hence creating the likelihood of interference demanded to stop the future seizure likelihood.

In 2023, Ghembaza and Djebbari [86] will implement an automatic task for the identification of epileptic seizures. The presented mechanism contained the time-frequency attributes of the EEG information. Experts estimated the functionality of the suggested approach using standard online sources. Experts estimated the time-frequency indications of the EEG information via QTFDs called SP, CWD, and SPWVD. Experts implemented a mechanism for identifying the activity of the epieptical brain by drawing out the related attributes from the attained representation of the time frequency. Moreover, experts evaluate the signals of the EEG in the 4 frequency bands according to the brainwave bandwidths called Gamma, Beta, Alpha, Theta, and Delta. Hence, experts discovered the shape of the ―time-frequency‖ region to explain the attributes within the plane of "time-frequency." Experts offered the extracted attributes of ―time-frequency‖ as inputs for the two mechanisms, such as SVM with the kernel function of the RBF and the KNN for the comparison requirements. Experts defined various attributes, and the research outcomes attained from the data sources displayed that the suggested mechanism offered very promising outcomes. Experts presented an effective mechanism for identifying epileptic seizures, and this mechanism localized the contour region at various stages on the representations of ―time-frequency of EEG signals‖ utilizing several quadratic distributions. Contrasted to the SP and the SPWVD, the CWD has confirmed its efficacy with more accuracy, denoting a potential approach for recognizing seizures by EEG signals.

2.2.3 Wavelet transform-based epileptic seizure detection

In 2023, Varlı and Yılmaz [24] have integrated the deep learning tasks that automatically identified the activity of the epileptic seizure, epileptic location identification and categorized the EEG signals by utilizing the images denoting the time-

frequency factors of the time sequences EEG signal and the original EEG signal's numerical values. The presented work adopted various benchmark sources and provided an integrated approach. The STFT and the CWT mechanisms were employed to change the signals to pictures. Two tasks were developed privately with the images implemented by the DTFT and CWT tasks. The experts created a mechanism that could identify where there was an activity of seizure in the EEG information, identify the epileptic location, and categorize the EEG signals.

In 2023, Amiri *et al.* [39] have demonstrated a framework for the automated identification of seizure from the EEG signal by employing the sCSP and the adaptive FSST. The sCSP was employed to choose the optimal channels and differentiate the seizure phases. To improve the representation of the ―time-frequency‖ of the various factor EEG signals and minimize the interferences and noise, the chosen channels were given to the FSST. The ―adaptive FSST's frequency spectrum‖ was split into diverse sectors focussed on a particular frequency to enrich the identification of seizure by employing the separation of the EEG signals to the seizure's rhythmic features. Hence, an effortless sequential classifier was all that was required to detect the seizures. The group of approaches was supported to extract the attributes from every segment's instantaneous frequency and amplitude and every chosen channel's log variance could be largely discriminative. Utilizing the sequential classifiers for these attributes prevented the training burden and the overfitting employ in various deep learning tasks and the non-sequential classifiers. The suggested mechanism was contrasted to the traditional high-functionality mechanisms utilizing the benchmark sources. This approach performed better concerning various factors. Therefore, the implemented approach's exemplary functionality illustrated that it could highly diminish the load of interpretation on clinicians and be a potential component for the detection of epilepsy.

In 2022, Narin [40] has deployed a 2D CNN and CWT mechanisms to forecast the "non-focal and focal epileptic seizure". The VGG16, ResNet50. Insceotion-ResNetV2, Inception V3, and Alex Net approaches have been employed to categorize the ―2D scalogram images‖ automatically into "non-focal and focal epileptic seizure". The functionalities of the five already trained approaches contrasted and the identification outcomes of the ―2D scalograms‖ were investigated. The best categorization correctness was attained by the Inception V3 network between the other employed 4 previously trained mechanisms. Hence, it might be considered that the previously learned approaches

and the ―2D scalogram‖ pictures of ―non-focal and the focal EEG signals‖ would be supportive to the clinicians for the robust and the rapid estimation of the epileptic seizure.

In 2020, Amin *et al.* [44] have recommended a CAD-aided DWT approach and arithmetic coding to discriminate the signals of epileptic seizure from the seizure-free signals. The suggested CAD approach included 3 stages. The initial stage separated the EEG signals into approximations and by employing DWT the detail coefficients decomposed while removing the unimportant coefficients in terms of threshold, hence restricting the amount of important wavelet coefficients. The next stage changed the important coefficients of wavelet to bit sequences employing the ―arithmetic coding‖ to estimate the ratio of compression. In the last stage, the compression attribute set was improvised. Experts employed the largely employed standard data source to contrast and estimate the approach with outcomes from the previous mechanisms. The recommended task attained better categorization functionality for the recognition of the seizures from EEG information, utilizing both ―non-linear and linear machine-learning‖ tasks. The CAD mechanism could hence be taken robustly with high identification ability that differentiated the activity of seizure from the normal and seizure-free EEG with other normal classifiers. The approach had the power for effective development as an adjunct to the medical epilepsy detection.

In 2022, Rout *et al.* [49] have integrated the MF-RDCNN and EWT mechanisms to develop a CAD model for the categorization of the epileptic seizure from the EEG signals. The EWT approach was employed with the EEG signals to draw out the three diverse BLMs and the suggested approach was employed to estimate the very significant ―unsupervised signatures‖ by considering the drawn out BLMs. The validation outcomes were performed utilizing three provided data sources to examine the efficacy of the designed work. The offered work's performance was higher against the other approaches and had overall average accuracy for the categorization issues utilizing the 10-fold cross- experiment. In addition, the suggested task has a good performance rate concerning the sensitivity, accuracy, and FPR by utilizing the information for training, and testing. After that, the residual information for the experiment from the overall information utilized with the data source. The lower the computational burden, the more the learning speed, the less event identification period, the higher the mean accuracy, and the exemplary overall functionality were the important merits of the recommended approach over other tasks for precise categorization of the seizure EEG records. The MF-RDCNN's digital framework

was also presented to implement a CAD model for the effective identification of the epileptic seizure activity.

In 2022, Sivasaravanababu *et al.* [73] have presented an end seizure indication framework that was automatic and the task was grounder by the deep learning. To attain this, the EEG signals from the traditional data sources. The DCVAE approach was employed to understand the provided seizure attributes from the EEG information and the TQWT was employed for the pre-processing operation. After that, these EEG features related to the seizures were offered as the input to the SB-LSTM approach for the epileptic seizures automatic identification. The approach attained better performance outcomes.

In 2022, Ghosh *et al.* [84] have decomposed the EEG signals into a "Beta band" employing the DWT. Moreover, experts contrasted the templates of the patients with the general template for the evaluation to attain the coefficients of wavelet cross coherence and WCS. Further, experts presented the PARAFAC design, time and frequency-points feature dimensions and a ―three-way tensor-aided channel representation‖ . In the end, experts adopted the ensemble methodology for choosing the ―seizure, onset, and seizure-free classes‖ . The medical source for this approach included six epileptic patients and five normal individuals. The categorization functionality of the WCS attributes on the PARAFAC approach for the identification of the seizure utilizing the ensemble bagged trees approach attained more accuracy. The outcomes have been contrasted with the other popular approaches. The goal was to evaluate the information against the three dimensions such as space, frequency, and time. The EEG-aided evaluation was important and efficient as an automatic approach for the identification of the seizure prior to its original manifestation.

2.2.4 Fuzzy-based epileptic seizure detection

In 2022, Shoeibi *et al.* [42] introduced a diagnostic approach by employing deep learning and fuzzy theory. The recommended task was estimated on the standard datasets with six categorization integrations and also on the standard data sources. The TQWT was employed to perform the EEG signal's decomposition into diverse subbands. In the stage of feature extraction, 13 diverse fuzzy entropies were estimated from distinct TQWT's sub-bands, and their computational burdens were estimated to assist the experts in selecting the optimal set for numerous approaches. Concerning this, an autoencoder was adopted for the reduction of dimensionality. Lastly, the modern ANFIS approach and its variants with the ―ANFIS-GOA, ANFIS-PSO, and the ANFIS-BS‖ approaches were

employed for the categorization. Utilizing the author's approach, the ANFIS-BS task has attained better accuracy in categorizing into two classes.

In 2023, Huang and Duan [43] presented a GFBLS approach to enhance the functionality of the FBLS according to the regularization of the graph. In addition, an effective GFBLS-aided mechanism was suggested for the recognition of IEDs from the EEG data. In the suggested task, the GCN was employed to draw out the attributes from the line graphs with the undirected links that were generated by the EEG data. Further extracted attributes by the GCN were subjected to the GFBLS for the identification of the IEDs. The research outcomes illustrated that the GFBLS count accomplished better performance rates that were better or had comparable functionality compared with the other traditional tasks.

2.2.5 Optimization algorithm-based epileptic seizure detection

In 2023, Pandey *et al.* [26] have presented a patient-generic mechanism to reduce the troubles presented in the existing works. In this work, various feature augmentation tasks were employed to generate a hybrid attribute space to obtain epileptic seizure non-linearity. This explained how the attribute space supported the predictor's ability to learn effectively to improve the prediction of seizures. Moreover, the predictor was tuned by employing the FB-SARO to enhance seizure estimation. After that, an optimal SPH was estimated via the learning of classifiers. The SPH supported obtaining early forecasting while securing accuracy and attaining a lower FPR. IT also supported notifying the patients with a better preparation period for the treatment. The recommended task was validated via online sources and contrasted with conventional methodologies.

In 2023, Chavan and Desai [27] have suggested an HMM-aided human learning optimization task to automatically identify the epileptic seizure by differentiating the non-focal and focal epileptic EEG signals. The HLO played an important role in the selection of electrodes that helped in the further task of feature extraction, minimized the approach's burden, and selected the features with the better qualities. The HLO-trained approach attained the feature vector created from the frequency-band-aided attributes, which were then adjusted utilizing the recommended task to enhance the identification performance. The learning and searching abilities of the individual were added to the implementation of the HLO approach, which supported the enhancement of system convergence. The epileptic seizure was mainly identified by utilizing the system, and the effectiveness of the

experiment was confirmed by estimating the evaluation factors. The HLO-trained approach was effective when compared to the traditional tasks.

In 2022, Bhandari and Huchaiah [63] intend to implement a seizure identification mechanism in the EEG signal utilizing advanced categorization and feature extraction mechanisms. The initial stage of the recommended task was signal pre-processing; after that, the integration of the DWT and the EMD was conducted for the decomposition of the signal. Further, the selection of features was conducted through the integration of the LDA and the PCA. With these selected attributes, an improvement was presented with the task of ―weighted feature selection," in that the weight was tuned with the aid hybrid approach called J-CSO. This hybrid approach was simple to develop with no additional attributes. It was simply applicable to present-time optimization issues. Because of these merits, the functionality of the provided work was more powerful than the existing tasks. Further, the J-CSO-aided I-ELM approach was presented in the identification stage that was suggested by three diverse tasks such as LSTM, DNN, and the fuzzy classifier. This was comparable to the correctness attained by traditional seizure identification tasks and this mechanism could support as an efficient component of clinicians for evaluating the large amount of data for enhancing the diagnosis of the seizures.

In 2023, Priyadarshini, and Reddy [66] have suggested a new AODTL-aided epileptic seizure categorization approach to detect the optimal balance among the hardware complexity and the classification accuracy. The recommended work has chosen the most effective attributes from the scalogram images utilizing the JSO. In addition, it finely tuned the hyper-attributes utilizing the OO. These two optimizers were employed to minimize the amount of attributes needed for the suggested AODTL approach; hence the computational complexity was minimized. The recommended task's implementation was performed in the "Xilinx" module and estimated in the standard data source. In the end, the outcome of the presented work displayed that the categorization and the diagnosis of the DTL approach with the highest accuracy could be attained. The highest performance was attained when experimenting with categorizing the epileptic seizures.

In 2023, Das and Nanda [82] have suggested a WELM mechanism, utilizing the BSC algorithm for the effective and rapid identification of the epileptic seizures and then the seizure-free epochs providing general temporal attributes. The recommended WELM-aided task allocated numerous weights to diverse classes to manage the biased-information issue normally discovered in the EEG information. In addition, the BCS algorithm was supported to select the better attributes for the enhancement of the model accuracy and

also to diminish the time of classification. A comparative experiment of the presented work with three conventional classifiers such as KNN, SVM, and the ELM was displayed utilizing the popular data sources. The research outcomes were expressed that the recommended approach has a very less false estimation rate and it performed better than the traditional approaches. Thus, this implemented mechanism has ensured itself as a robust and fast patient-dependent approach to identifying the seizure and seizure-free epochs.

2.2.6 Miscellaneous-based epileptic seizure detection

In 2023, Ding *et al.* [30] have designed a privacy-securing Fed-ESD mechanism from the EEG signals in the fog computing-aided IoMT. An efficient and lightweight "spatiotemporal transformer network" was suggested to understand the ―temporal and spatial‖ representations from the general information of every patient. The recommended Fed-ESD utilized the fog nodes as normal collectors to perform location-sharing-aided EEG signals for the applications of IoMT. In addition, a greedy mechanism was presented for deciding the best fog node for the overall aggregation during the learning stage. The numerical estimations illustrated the efficacy of the suggested approach concerning detection functionality, scalability, stability, and resource efficacy for the IoMT deployment.

In 2024, Xiao *et al.* [55] presented a SSL task for the detection of EEG-aided seizures. It resolved the issue of ineffective annotated information by employing a larger number of unlabeled pieces of information for the training stage. To draw out the EEG signal's global dependency, experts utilized the attention operation-aided transformer as the core and called the task SLAM for the identification of EEG-aided seizures. Both the cross-patient and patient-dependent seizure identification validations were conducted on the standard data source. The research outcomes validated the SLM task's efficacy.

In 2023, Baghdadi *et al.* [67] have designed a patient-independent schema for the categorization of the seizure kind and offered more attention to the fundamental attention task's ability to explain the suggested work. Utilizing a channel-aided attention task, an EEG signal's quantification was enabled. Hence, the outcomes became very interpretable, and brain lobe visualization by the seizure kinds was permitted. Experts estimated the presented work for seizure identification and kind categorization. The expert's approach was capable of categorizing the eight seizure kinds with higher accuracy than the original EEG information without any pre-processing tasks. The study displayed the correlation

between the baselines of neurology and the interpretable outcomes of the recommended work.

2.3 Research Gaps and Challenges

Epilepsy is a neurological situation created due to the immediate firing and the brain neuron's impromptu discharge. High enhancement of the sick persons explains the importance of the automated seizure identification mechanism. Experiments have pointed to machine learning mechanisms for the automatic recognition of the seizures by EEG signals. These mechanisms include SVM, PNN, ANN, MLP, KNN, ELM, GBA, DT, Bayes Net, and so on. In compare to the manual labelling, identification by the machine learning mechanisms is very consistent and faster. But these approaches demand a handcrafted attributes and sophisticated attribute selection and ranking approaches. The systematic evaluation of the conventional works on the seizure identification explains that various machine learning approaches utilize the handcrafted features and the complex attribute selection approaches for the seizure identification. In addition, the approaches that utilize the KNN though process on original images however lack the generalization on the medical data sources and in certain cases result in low identification accuracy. Though various experiments have presented ―wavelet transforms to EEG signals‖, these approaches either employed an improved ―wavelet transform‖ like ―complex wavelet transform‖, or wavelet packet decomposition that are not always compatible with the 1D signal processing and that require residual proceeding and loading period.

In addition, some of the works only categorized the seizure and normal EEG activity yet did not categorize the seizure-free time slots. Also, though there are various promising results in the seizure detection approaches, a numerous improvements remain and may be achieved. Initially, some of these approaches are according to the CNNs that explore a similar pattern against the EEG signals attained from diverse individuals without considering the merits of ―temporal‖ samples in the EEG signal. Then, the next issue is the assumption that a very complex and deep KNN framework must be enough effective to gather the overall significant data needed for identifying the epileptic seizures. But, enhancing the network dimension takes large attributes that require to be considered and thus enhances the probability of overfitting. Further, with conventional deep learning attributes and the fundamental framework, it doesn't produce good outcomes. The past years have experimented with effective seizure identification utilizing diverse kinds of approaches. Automated seizure identification includes two primary stages. Processing and

analysis of the signals for the related attributes are utilizing the initial stage for the detection. Conventional classifiers normally employ the two phases for the automated seizure categorization. The present seizure identification approaches according to the deep learning tasks that achieved effective outcomes however, as seen various techniques highly depend on the CNN framework. In some of the experiments, attributes are extracted utilizing the CNN and further employed in the conventional classifiers for the categorization.

Normally, the CNN utilizes the spatial data from the EEG signal for identifying the seizure dynamics. The EEG signals are ―non-linear‖ so extraction and isolating the temporal attributes of the brain activities utilizing CNN can meet several restrictions. In several traditional short-term Fourier transformations, and the ―wavelet transform‖ has been employed to estimate the EEG signal's ―time-frequency‖ coefficients and to change signals into gray pictures. These outcomes are further employed as input in the 2D CNN for extracting the spatial and spectral data to detect the seizures. The limitation of certain mechanisms is that 1D EEG signals are changed into 3D pictures or matrices that demand an extra processing period and also enhance the data volume. Another limitation of the conventional mechanism is various approaches are channel-oriented, i.e., initially, it chooses the channels and further utilizes these chosen channel attributes as input to the identification of the seizure. Training the deep learning mechanisms frequently demand partitioning the EEG into small parts normally among 0.5 and 30 seconds. The categorization factors of those separate parts is a significant phase to classify the system functionality but experts concentrate on offering a system for the seizure identification one must assess the functionality of the more EEG signal's stretches conducting the transitions among the ictal and the interracial stages. Considering that the block box character of the deep learning is a general issue to the transfer of developments in the medical sectors, experts concentrated on discovering not just the attributes understood by the deep learning task but also the given information features resulting in the categorization decision with the aim to enhance the method validity and powerfully learning the related pathology. Since attributes in the deep learning tasks are automatically drawn out during the training phase with the absence of human interventions, the results are rarely interpretable for the experts. Several experiments still advance to define the dynamics of networks when executing the EEG signals.

2.4 Summary

This chapter has observed the classical epileptic seizure detection mechanisms that have achieved more attention in the bio-medical sector. This presented work was categorized as an efficient way for understanding and making decisions for the seizure detection tasks. This was very supportive work however it required more improvements that were directed to develop an advanced seizure mechanism for the presented epileptic seizure identification mechanism.

Chapter 3

Improved Ensemble Learning Model with Optimal Feature Selection for Automated Epileptic Seizure Detection

3.1 Introduction

This chapter introduces an innovative approach to the detection of epileptic seizures by leveraging an I-ELM. The recommended model is structured around five key stages: "pre-processing, signal decomposition, feature extraction, optimal feature selection, and detection." Initially, EEG signals are obtained from dual online sources and preprocessed using the STFT technique. The signal decomposition step employs the DWT. Subsequently, spatial and temporal feature extraction techniques are applied to the decomposed signals. For precise choice of features, a novel meta-heuristic method called the M-TSA is utilized to control training difficulty and improve detection effectiveness. After that, the I-ELM uses these carefully selected characteristics to detect seizures by using three primary classifiers: LSTM [95], fuzzy [93], DNN [94], and ELM [96]. The novel I-ELM method is developed based on the top-performing ensemble classifiers identified through the recommended M-TSA, allowing it to effectively detect seizures from EEG signals [97]. The effectiveness of the recommended model is validated through experiments conducted on various EEG datasets. Comparative analysis with traditional models demonstrates the effectiveness of the recommended approach in classifying epileptic EEGs. These results underscore the powerful capacity of the proposed method in automated seizure detection.

3.2 Proposed Methodology

3.2.1 Systematic recognition of automatic epileptic seizure utilizing EEG signals

Detecting transient phenomena such as epileptic seizures is a significant challenge for physicians due to their infrequent occurrence, leading to misdiagnosis and inappropriate detection [101]. Epileptic seizures often resemble other clinical events, like epileptic or non-epileptic seizures, further complicating accurate identification. EEG signals offer a means to identify epileptic patients, but they present challenges as they are noisy, non-stationary, involve large amounts of complex data, and are non-linear [102]. However, these models are laborious and time-consuming, making the timely detection of seizures a challenge [103]. The key difficulty lies in classifying EEG signals into ictal and interictal states for epileptic patients. Additionally, selecting the appropriate classifiers and

features further complicates the task. Machine learning-based strategies have been employed to study EEG signals, aiming to enhance classification accuracy [104]. Therefore, there is a pressing need to develop an epilepsy diagnosis method that offers high accuracy while minimizing time consumption. Such a model would significantly reduce the complexity associated with seizure-related diagnoses, as illustrated in Figure 3.1.

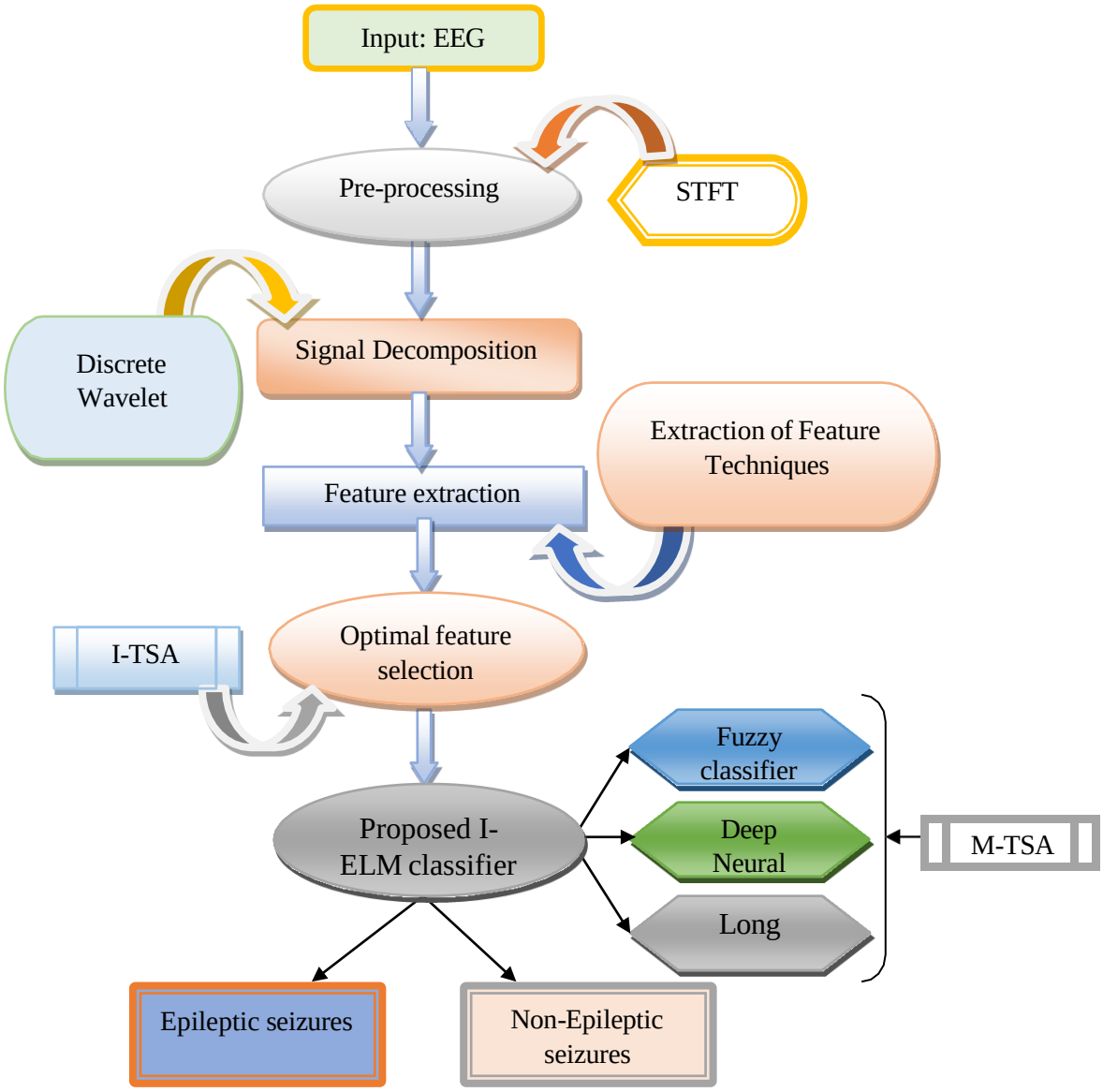

Figure 3.1: Recommended detection of automatic epileptic seizure method

The detection model of epileptic seizure recommended in this study utilizes EEG signals from patients with epilepsy. The detection process involves five key stages: "pre-processing, signal decomposition, feature extraction, optimal feature selection, and

detection." In the stage of pre-processing, the STFT method is employed to obtain amplitude-spectrogram modulation, effectively eliminating the noise and changing the data into true neutral signals. The beforehand processed EEG signals are then subjected to signal deconstruction using the DWT approach, producing a succession of continuous-frequency signals. In the following step, the EEG signals' spectrum and timing properties are obtained using the proper methods. These extracted features are further refined and optimized utilizing the M-TSA, which selects the necessary attributes from the signals of the EEG. The recognition process utilizes the recommended I-ELM classifier. This classifier incorporates DNN, LSTM classifiers, and fuzzy in conjunction with M-TSA. In this phase, both the LSTM and DNN classifiers maximize the total number of neurons concealed, while the fuzzy classifier optimizes the parameters they use. Precise and accurate resolution of multifaceted functions is the main goal of the optimization procedure. The EEG data are then classified using algorithms that use ensemble learning to ascertain if they are indicative of non-epileptic or epileptic seizures.

3.2.2 Datasets Definition

The recommended method for detecting epileptic seizures has obtained input images from dual databases, ―Physionet and GitHub,‖ that are mentioned below.

Dataset 1: This database was sourced from "https://physionet.org/content/chbmit/1.0.0/," with the access date noted as November 7, 2023. This dataset, obtained from the "Children's Hospital Boston," comprises EEG seizure recordings from patients. Dataset 1, under consideration, consists of 22 patients from 23 cases. Five male and seventeen female patients, ranging in age from 3 to twenty-two for men and 1.5 to 19 years for the females, comprise these instances. A total of 198 EEG signals from seizures are included in Dataset 1.

Dataset 2: This database was obtained from "https://github.com/akshayg056/Epileptic-seizure-detection," with the access date recorded as November 7, 2023. This dataset comprises data from 500 individuals, each with 4097 data points. The EEG recordings are represented as data points, with each recording having a length of 23.6 seconds. In each recording, 178 points of data are categorized into columns of five.

Dataset 3: Dataset 3: The input signals were sourced from "https://data.mendeley.com/datasets/5pc2j46cbc/1." This dataset comprises EEG recordings from six patients, captured at the Observing Epilepsy Unit of the "American University of Beirut Medical Centre." The data encompasses measurements from 21 scalp electrodes, following the

electrodes of 10–20 system placements, and the sampled frequency is 500 Hz. The entire set of channels undergoes band-pass filtering ranges of 70 Hz and 1/1.6 Hz, effectively eliminating the electrical utility frequency of 50 Hz.

The gathered input signals are recorded as a data set, which is symbolized by $m = 1,2...M$, where m represents the overall number of signals in the data and M indicates the overall quantity of signals.

3.2.3 Pre-processing Signal

In the signal processing stage, unidentified artifacts present in the EEG signal are effectively removed before being passed on to the subsequent processing step. This signal processing operation is carried out using an analysis of time-frequency, which quantifies the energy density function over frequency and time [105]. The analysis involves examining the similarity in signal frequencies during non-stationary signal periods. A method commonly employed for this purpose is the STFT [99], which provides complex amplitude information concerning time and frequency for any given signal. STFT analysis facilitates the localization of time-specific frequency data within non-stationary signals. Let us consider a signal with an intercept, denoted by Eq. (3.1).

$$E(s) = t(s) + p(s) \tag{3.1}$$

In this context, the variable $t(s)$ expresses the noise and $p(s)$ represents the signal of channel interest. The formulation for the STFT is provided in Eq. (3. 2).

$$F(s, p) = \int z(s_1)\, i*(s_1 - s)\, t^{(k\,2\Pi g q_1)}\, y s_1 \tag{3.2}$$

In Eq. (3.2), the term $\int z(s_1)\, i*(s_1 - s)$ represents the signal frequency position at time s_1. The function of the window is expressed as $t(s)$ and the signal interception is represented by $p(s)$at time s_1 . Following preprocessing, the EEG signals, denoted as K_m^{pr} are then advanced to the signal decomposition stage.

3.2.4 Feature extraction for the Detection of Epileptic Seizure and EEG signal decomposition utilizing DWT and STFT.

3.2.4.1 DWT for Signal Decomposition

The preprocessed EEG signal undergoes decomposition to separate its components assisted on different bands of frequency. Utilizing DWT, the EEG signals are effectively decomposed.

The DWT is a powerful technique for decomposing signals into their constituent components at different scales, which can be invaluable for a wide range of signal processing and analysis tasks. Its ability to provide multi-resolution representations makes it a versatile tool in various fields, including audio analysis, data compression and image processing.

3.2.4.2 Extracting Feature Technique

The feature extraction process is pivotal in improving the accuracy of signal recognition by capturing distinct spectral and temporal characteristics from decomposed EEG signals. This critical phase of feature extraction involves the utilization of two primary techniques: spectral and temporal feature extraction [108]. Temporal features are concerned with the time-based attributes of EEG signals, while spectral features are associated with their frequency-based attributes. Temporal features are quantified by utilizing metrics such as standard deviation, minimum amplitude and mean amplitude for each signal decomposing [109].

Feature extraction is a fundamental step in data preprocessing that plays a crucial role in making data more manageable, informative, and suitable for analysis and modeling. It serves as a bridge between raw data and effective data-driven insights or machine learning applications [110]. Lastly, the best selection of feature technique is applied to the features extracted.

3.2.5 Recommended epileptic automatic seizure detection

3.2.5.1 Optimal Selection of Feature

Effective selection of features is crucial for learning-based methods to achieve performance of satisfactory classification. In the context of the recommended M-TSA, optimal feature selection plays a key role in lowering the length of extracted attributes. This not only conserves computational resources but also minimizes training complexity, leading to improved performance of detection [111]. The better attributes are expressed as $FM_{fs^*}^{opt,}$ where $fm^* = 1,2,\square, FM^*$ and FM^* specifies the total amount of M-TSA-collected optimum characteristics. The best features in this instance have been determined as 10. Traditional optimal feature selection algorithms face challenges. For instance, MRFO encounters critical real-world benefits and issues, HGSO reduces categorization

performance while maximizing the total count of features, Global capability is impacted by SCHHO, which also generates extensive optimization operations, and method resilience is reduced by GOA [112]. These challenges hinder the accurate attainment of feature selection performance. To address these issues, the novel M-TSA is suggested as a population-based optimization algorithm. M-TSA effectively mitigates optimization challenges and enhances the selection of feature model accuracy. Consequently, it demonstrates the potential to yield accurate features when compared with traditional algorithms [113]. Reducing data dimensionality and strengthening the stability of classification algorithms are the main goals of choosing features.

3.2.5.2 Modified TSA

This paper proposes an epileptic seizure identification approach that optimizes the features obtained for the optimum choice of features using M-TSA. M-TSA is used to constrain variables in fuzzy logic, LSTM networks, and neurons that are concealed by DNNs. In the epileptic seizure recognition approach, this method produces enhanced efficiency and higher precision for detection [114]. Although TSA provides extreme accuracy resilience and optimal answers regardless of search space and the number of dimensions, it encounters interactions between pursuit agents. To address this limitation, the new algorithm M-TSA is created to overcome these problems and enhance the overall efficiency of the epileptic seizure detection system [115].

TSA [92] draws inspiration from the survival mechanisms of tunicate animals residing in the depths of the ocean. These unique creatures possess the ability to emit pale blue-green light, enhancing their visibility over considerable distances. By drawing in seawater and utilizing jet propulsion, tunicates can move autonomously through the ocean. Remarkably, tunicates are the only marine animals capable of traversing vast oceanic expanses using their jet propulsion behavior. Additionally, tunicates exhibit swarm behavior, which, coupled with their jet propulsion, aids them in migrating across the ocean to locate their food sources, representing optimal solutions within the search space. The success of tunicates in their search for food depends on fulfilling three crucial conditions: propagating positions towards the best search agents, ensuring that positions remain close to the agents of optimal finding, and avoiding conflicts among search agents.

To find the best answer among a set of agents, a population and its parameters are created in the first stages of the suggested M-TSA. A search agent is deemed to be the most effective one if the latest iteration of the algorithm surpasses the highest permitted iteration count. Random quantities are used to estimate every search agent's efficiency and

randomized index [116]. While regular TSA uses random numbers for location updates, the M-TSA is used to update the swarm's location. The discovered agent's position is then shifted in the direction of the top search engines when a specific requirement is satisfied. At last, the final best approach is obtained by computing the value of fitness for every updated searcher's agent. The pseudo-code for the recommended M-TSA is outlined in Algorithm 3.1

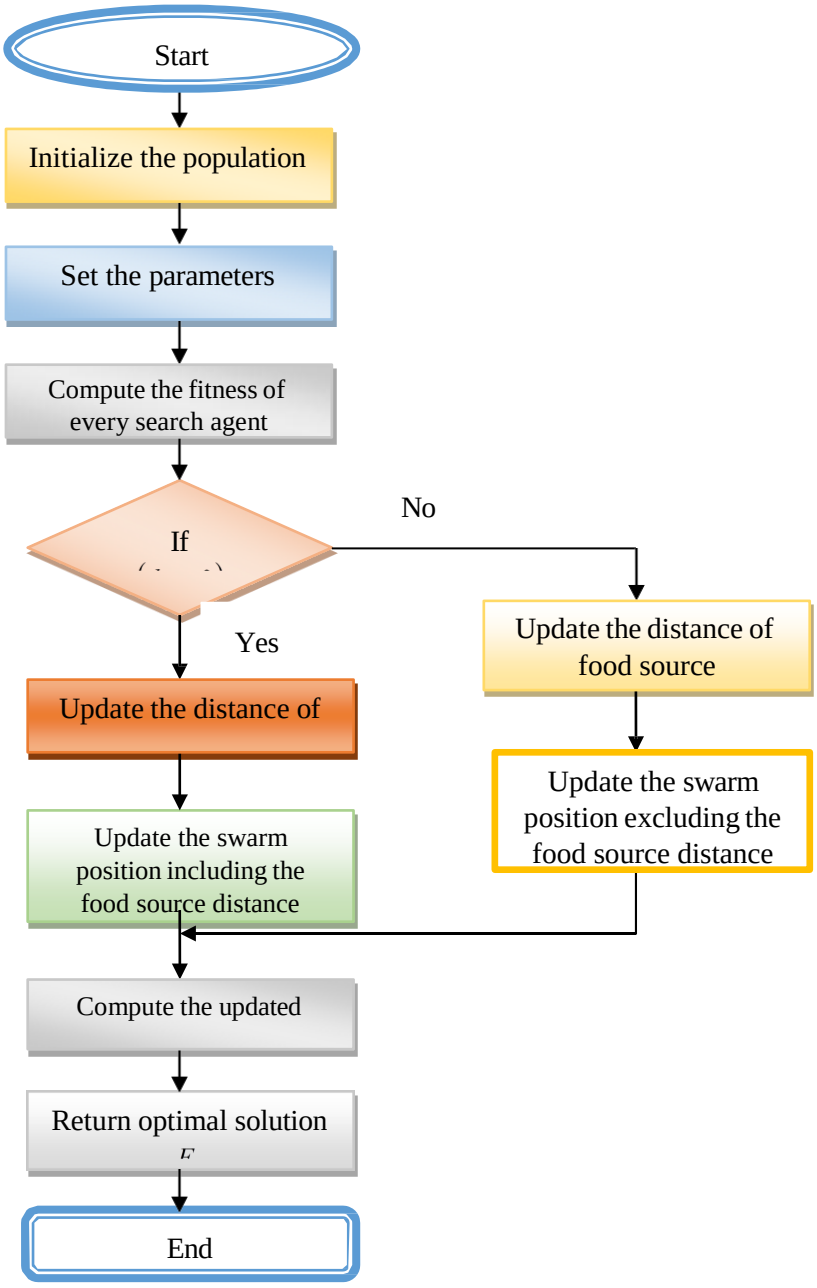

Figure 3.2: The investigated M-TSA approaches flowchart

Algorithm 3.1: Recommended M-TSA

Assume the parameters L, Y, u, m and ma_i

Assume $xx_{\min} = 1$

Assume $xx_{\max} = 10$

While $(t < ma_i)$ do

For $i = 1 to\ xx_{\max}$

For $j = 1 to \dim_{space}$

The value of fitness is computed

If $(e_3 \geq 0)$

Adjust the food source distance following the initial constraint of Eq. (3.16).

Revise the swarm's position as dictated by Eq. (3.17).

Else

Modify the food source distance according to the second constraint specified in Eq. (3.18).

Adjust the location of the swarm following Eq. (3.19).

End if

End for

Revise the location of the ultimate tunicate according to the equation presented in Eq. (3.19).

The parameters are updated

$t = t + 1$

End while

Return better value F_m

End

3.2.5.3 Developed Model of Ensemble Learning

The recommended I-ELM receives optimal features FM_{fs*}^{opt}, improving the prediction performance and classification of the model while reducing poor selection. The epileptic detection system in this proposal employs an ensemble learning approach integrating three classifiers: DNN, LSTM, and fuzzy classifiers. This optimization process significantly boosts the classification accuracy of the system [117].

Fuzzy Classifiers [93]: In the classification process, fuzzy classifiers are utilized to distinguish epileptic seizures. The set of fuzzy theory enables the manipulation and expression of ambiguity and uncertainty within the system.

DNN Classifiers [94]: The classifiers of DNN are created with dual hidden neurons to improve the categorization training speed and precision of the EEG signals.

LSTM Classifier [95]: An RNN-based structure, the LSTM is also used in the development of classifications. It is employed to improve the method of categorization.

Figure 3.3 shows the suggested I-ELM as an epilepsy detection technique.

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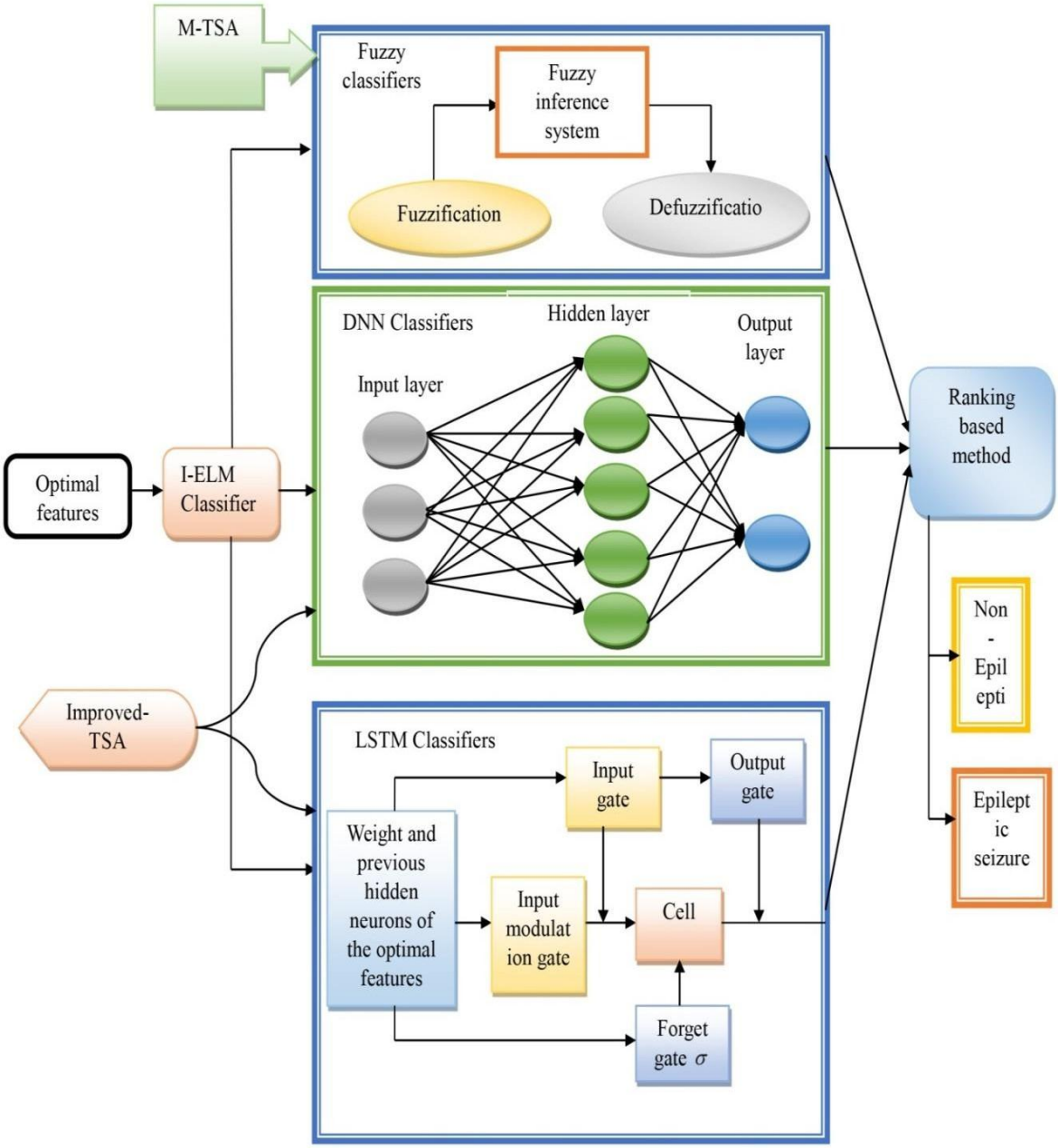

Figure 3.3 The Suggested Epileptic Seizure Identification Model's Enhanced Ensemble Learning Approach

To classify the properties derived from the electrical brain wave signals, the best features are fed through the I-ELM classifier. The three classifiers in the I-ELM accomplish this, increasing its categorization accuracy. The fuzzy classifiers first use the most effective features. The M-TSA is used to determine the member range of the fuzzy, which then yields a result indicating whether the convulsions are psychotic or not. Then,

by enhancing the undetected neurons in the network, one improves the classification algorithm using DNN, learns new models, provides precise variables, and gives improved outcomes in terms of a seizure of epilepsy or non-epileptic wave [119]. Ultimately, the ideal attributes are classified using the LSTM neural network model, which optimizes the neurons that are concealed and outputs for a non-epileptic or epileptic seizure. The final identification result is derived from the outcomes of the three classifiers. The aforementioned three classifiers are used in a ranking system, where the findings with the greatest value are regarded as the best option for either having a non-epileptic or epileptic seizure. Based on the chosen optimal features, multi-objective function optimization is carried out in the classification process [120].

The primary characteristic of the ideal feature choice method is its ability to prevent problems with overfitting. It shortens the training period and increases precision. It improves the recommended method's identification. Compared to the other traditional heuristic methods, the altered TSA is more effective [121]. This is because it has the capacity to tolerate faults and can generate the desired results with smaller mistakes. Its maximum precision was achieved, its mistake rate is minimal, and its application potential is strong. A combined learning approach is an artificially intelligent procedure that combines several algorithms for learning in a deliberate way to improve the accuracy of predictions. When opposed to using a single model, the precision and adaptability of ensemble approaches are its primary advantages [122].

3.2.5.4 Objective Model

The suggested epileptic detection of seizures approach employing EEG signals has a multi-objective role that is carried out by M-TSA during the categorization phase. To improve classifier precision and accuracy, M-TSA is used for maximizing the unseen neurons of the LSTM and DNN as well as the fuzzy joining limit. Eq. (3.3) provides a goals function for the proposed technique.

$$of_{fnc} = \underset{\{o_{ftr},\mu_I(y),uy_{DNN},uy_{LSTM}\}}{\arg\max} \left(AA_r + PP_V\right) \tag{3.3}$$

The expression, in this case, $\mu_I(y)$ denotes the fuzzy boundary variables, opt_{ftr} the best characteristics chosen are indicated by uy_{DNN} and uy_{LSTM}, accordingly, which stand in for the concealed neurons of the LSTM and DNN. Ten parameters are found to be the perfect number, and the fuzzy classifier's inclusion limits fall between 0.1 and 0.9. For

every classifier, the concealed neurons of the LSTM and DNN spread within a time window [124].

3.3 Results and Discussions

3.3.1Experimental Setup

The suggested EEG-based epileptic seizure identification technique was created using a Python Anaconda program and subjected to experimental evaluation. The proposed model and the current methodology were tested using both Type 1 and Type II parameters. ―Specificity, precision, NPV, sensitivity, F1 score, and MCC‖ are examples of type I statistics that were designated as positive measures. FNR, FPR, and FDR are examples of Type II measurements that were used as negative metrics. To perform the simulation, the entire population of 10 was taken into account for the epileptic detection categorization. The suggested M-TSA-I-ELM approach was examined in comparison to other classifiers based on machine learning such as DNN [94], fuzzy [93], I-ELM [96], and LSTM [93], as well as alternative algorithms such as GWO [90], PSO [89], WOA [91], and TSA [92].

Table 3.1: Heuristics algorithm-based algorithmic evaluation of the detection of epileptic seizure models using datasets 1 and 2

Dataset 1					
Algorithms	PSO-I-ELM [27]	GWO-I-ELM [28]	WOA-I-ELM [29]	TSA-I-ELM [26]	PROPOSED M-TSA-I-ELM
Accuracy	0.9488	0.955793	0.94803	0.968415	0.969659
Sensitivity	0.967185	0.975432	0.967305	0.987404	0.9892
Specificity	0.499246	0.484444	0.499281	0.515464	0.498512
Precision	0.979266	0.978452	0.978249	0.979842	0.979407
FPR	0.500754	0.515556	0.500719	0.484536	0.501488
FNR	0.032815	0.024568	0.032695	0.012596	0.0108
NPV	0.499246	0.484444	0.499281	0.515464	0.498512
FDR	0.020734	0.021548	0.021751	0.020158	0.020593
F1-score	0.973188	0.97694	0.972746	0.983609	0.984279
MCC	0.411371	0.444422	0.417941	0.554581	0.55706
Dataset 2					

Algorithms	PSO-ELM [27]	GWO-ELM [28]	WOA-ELM [29]	TSA-ELM [26]	PROPOSED
Accuracy	0.964267	0.955674	0.957037	0.954785	0.967881
Sensitivity	0.983393	0.975224	0.975628	0.973699	0.986498
Specificity	0.506647	0.497101	0.505988	0.50295	0.50687
Precision	0.979463	0.978489	0.979556	0.979079	0.980213
FPR	0.493353	0.502899	0.494012	0.49705	0.49313
FNR	0.016607	0.024776	0.024372	0.026301	0.013502
NPV	0.506647	0.497101	0.505988	0.50295	0.50687
FDR	0.020537	0.021511	0.020444	0.020921	0.019787
F1-score	0.981424	0.976854	0.977588	0.976381	0.983346
MCC	0.514376	0.455622	0.460691	0.449378	0.536202

3.3.2 Efficiency analysis of the recommended detection of epileptic seizure method in terms of different classifiers

As shown in Table 3.2, the suggested epileptic detection model is tested using two distinct data sets, such as dataset 1 and dataset 2, using several traditional classifiers.

Table 3.2 : Based on an established learning structure, classification evaluation is performed on the epileptic seizures detecting model using datasets 1 and 2.

Dataset 1					
Classifiers	Fuzzy [30]	DNN [31]	LSTM [32]	ELM [33]	PROPOSED
Accuracy	0.948681	0.937896	0.931496	0.931259	0.969659
Sensitivity	0.985507	0.974282	0.96644	0.966902	0.9892
Specificity	0.50039	0.495713	0.49881	0.498833	0.498512
Precision	0.96002	0.959149	0.959802	0.959028	0.979407
FPR	0.49961	0.504287	0.50119	0.501167	0.501488
FNR	0.014493	0.025718	0.03356	0.033098	0.0108
NPV	0.50039	0.495713	0.49881	0.498833	0.498512
FDR	0.03998	0.040851	0.040198	0.040972	0.020593
F1-score	0.972597	0.966656	0.96311	0.962949	0.984279
MCC	0.582935	0.518702	0.484879	0.488819	0.55706

Dataset 2					
Classifiers	Fuzzy [30]	DNN [31]	LSTM [32]	ELM [33]	PROPOSED
Accuracy	0.930489	0.955793	0.927644	0.949037	0.967881
Sensitivity	0.965274	0.992569	0.962145	0.985381	0.986498
Specificity	0.501973	0.501976	0.501188	0.505864	0.50687
Precision	0.959801	0.960928	0.959747	0.9605	0.980213
FPR	0.498027	0.498024	0.498812	0.494136	0.49313
FNR	0.034726	0.007431	0.037855	0.014619	0.013502
NPV	0.501973	0.501976	0.501188	0.505864	0.50687
FDR	0.040199	0.039072	0.040253	0.0395	0.019787
F1-score	0.96253	0.976492	0.960944	0.972781	0.983346
MCC	0.483201	0.631533	0.470069	0.586376	0.536202

3.3.3 Using different algorithms, performance analysis on the Epileptic EEG dataset

In terms of accuracy, the performance analysis of the proposed M-TSA-I-ELM method on the Epileptic EEG Dataset compared it to several existing optimization algorithms. At learning percentage 40, the suggested method outperformed PSO-I-ELM, GWO-I-ELM, WOA-I-ELM, and TSA-I-ELM by 2.62%, 2.22%, 2.02%, and 1.37%, respectively. Thus, at learning percentage 60, the proposed M-TSA-I-ELM technique achieves 55.55%, 64.28%, 56.98%, and 73.68% less FNR than PSO-I-ELM, GWO-I-ELM, WOA-I-ELM, and TSA-I-ELM, respectively. Therefore, it is verified that, for dataset 3, the suggested M-TSA-I-ELM technique performs better than the other current traditional algorithms

3.3.4 Evaluation of epileptic EEG dataset performance using different classifiers

The performance analysis on the Epileptic EEG Dataset for the proposed M-TSA-I-ELM method of epileptic seizure detection with different existing classifiers shows that, at learning percentage 40, the suggested method outperforms PSO-I-ELM, GWO-I-ELM, WOA-I-ELM, and TSA-I-ELM by 2.62%, 2.22%, 2.02%, and 1.37%, respectively, in terms of sensitivity. Thus, at learning percentage 60, the proposed M-TSA-I-ELM technique achieves 55.55%, 64.28%, 56.98%, and 73.68% less FNR than PSO-I-ELM, GWO-I-ELM, WOA-I-ELM, and TSA-I-ELM, respectively. Therefore, it is verified that,

for dataset 3, the suggested M-TSA-I-ELM technique performs better than the other current traditional algorithms.

3.3.5 Using several classifiers, performance analysis of an epileptic EEG dataset

According to a performance analysis conducted on the Epileptic EEG Dataset, the suggested M-TSA-I-ELM method outperforms other existing classifiers in terms of sensitivity. At learning percentage, it outperforms Fuzzy, DNN, LSTM, and ELM by 4.65%, 5.28%, 5.09%, and 3.39%, respectively.

Table 3.3: Based on an established learning framework, classification analysis of the epileptic seizures detection model using datasets 1 and 2

Dataset 1					
Algorithms	Fuzzy (Rabcan et al. 2020)	DNN (Xu et al. 2020)	LSTM (Nakisa et al. 2018)	ELM (Zhou et al. 2020)	PROPOSED
Accuracy	0. 948681	0. 937896	0. 931496	0. 931259	0. 969659
Sensitivity	0. 985507	0. 974282	0. 96644	0. 966902	0.9892
Specificity	0. 50039	0. 495713	0. 49881	0. 498833	0. 498512
Precision	0. 96002	0. 959149	0. 959802	0. 959028	0. 979407
FPR	0. 49961	0. 504287	0. 50119	0. 501167	0. 501488
FNR	0.014493	0.025718	0.03356	0.033098	0.0108
NPV	0. 50039	0. 495713	0. 49881	0. 498833	0. 498512
FDR	0.03998	0.040851	0.040198	0.040972	0.020593
F1-score	0. 972597	0. 966656	0. 96311	0. 962949	0. 984279
MCC	0. 582935	0. 518702	0. 484879	0. 488819	0. 55706
Dataset 2					
Algorithms	Fuzzy (Rabcan et al. 2020)	DNN (Xu et al. 2020)	LSTM (Nakisa et al. 2018)	ELM (Zhou et al. 2020)	PROPOSED
Accuracy	0. 930489	0. 955793	0. 927644	0. 949037	0. 967881
Sensitivity	0. 965274	0. 992569	0. 962145	0. 985381	0. 986498
Specificity	0. 501973	0. 501976	0. 501188	0. 505864	0. 50687
Precision	0. 959801	0. 960928	0. 959747	0.9605	0. 980213

FPR	0. 498027	0. 498024	0. 498812	0. 494136	0. 49313
FNR	0.034726	0.007431	0.037855	0.014619	0.013502
NPV	0. 501973	0. 501976	0. 501188	0. 505864	0. 50687
FDR	0.040199	0.039072	0.040253	0.0395	0.019787
F1-score	0. 96253	0. 976492	0.960944	0. 972781	0. 983346
MCC	0. 483201	0. 631533	0.470069	0. 586376	0. 536202

Table 3.4. Comparative analysis on epileptic seizures detection model with recent literature for dataset 1.

Dataset 2					
Algorithms	TQWT (HASSAN ET AL. 2016	EL-LPBOOST (HASSAN AND SUBASI 2016	ADAPTIVE -EL (HASSAN ET AL. 2019	ANN (HASSAN AND HAQUE 2015)	PROPOSED M-TSA-I-ELM
Accuracy	0. 93677	0.9464	0.936	0. 957896	0. 976593
Sensitivity	0. 972939	0. 973978	0. 972114	0. 976613	0. 995626
Specificity	0. 496481	0. 500551	0. 494115	0. 504065	0. 496894
Precision	0. 95922	0. 968982	0. 959202	0. 979486	0. 980345
FPR	0. 503519	0. 499449	0. 505885	0. 495935	0. 503106
FNR	0.027061	0.026022	0.027886	0.023387	0.004374
NPV	0. 496481	0. 500551	0. 494115	0. 504065	0. 496894
FDR	0.04078	0.031018	0.040798	0.020514	0.019655
F1-score	0. 966028	0. 971471	0. 965609	0. 978037	0. 987926
MCC	0. 513572	0. 491874	0. 507912	0. 468689	0. 62722

Table 3.5. State-Of-Art comparisons on epileptic seizures detection model with recent literature for dataset 2.

Dataset 2					
Algorithms	TQWT (HASSAN ET AL. 2016	EL-LPBOOST (HASSAN AND SUBASI 2016	ADAPTIVE -EL (HASSAN ET AL. 2019	ANN (HASSAN AND HAQUE 2015)	PROPOSED M-TSA-I-ELM
Accuracy	0. 941096	0. 951852	0. 950133	0. 946785	0. 979259
Sensitivity	0. 977023	0. 979841	0. 986638	0. 965577	0. 998335
Specificity	0. 500802	0. 496553	0. 50177	0. 498508	0. 507622
—Precision	0. 959979	0. 969527	0. 960509	0. 978691	0. 980442
FPR	0. 499198	0. 503447	0. 49823	0. 501492	0. 492378
FNR	0.022977	0.020159	0.013362	0.034423	0.001665
NPV	0. 500802	0. 496553	0. 50177	0. 498508	0. 507622
FDR	0.040021	0.030473	0.039491	0.021309	0.019558
F1-score	0. 968425	0. 974579	0. 973398	0. 972089	0. 989308
MCC	0. 535522	0. 515118	0. 590783	0. 406848	0. 676842

at learning percentage 75, the proposed M-TSA-I-ELM technique achieves 45.67%, 44.89%, 27.51%, and 24.12% enriched ness in precision compared to Fuzzy, DNN, LSTM, and ELM, respectively. Therefore, it is verified that, for dataset 3, the suggested M-TSA-I-ELM model is more advanced than the other current classifiers.

3.3.6 Overall performance analysis on epileptic EEG dataset

Table 3.6 displays the overall efficacy analysis on the Epileptic EEG Dataset for the proposed epileptic seizure detection approach using a variety of current traditional algorithms and deep learning techniques. The suggested M-TSA-I-ELM approach outperforms PSO-I-ELM, G W O -I-ELM, W O A -I-ELM, a n d TSA-I-ELM by3.15%,6.68%,3.10%, and 2.99%, respectively, according to Table 6's accuracy results. Similarly, the proposed M-TSA-I-ELM technique achieves 25.69%, 12.79%, 32.41%, and

34.52% enrichedness in terms of the FPR, compared to Fuzzy, DNN, LSTM, and ELM, in that order. Therefore, it is demonstrated that, for dataset 3, the proposed M-TSA-I-ELM technique is more enriched than the other traditional deep learning methods.

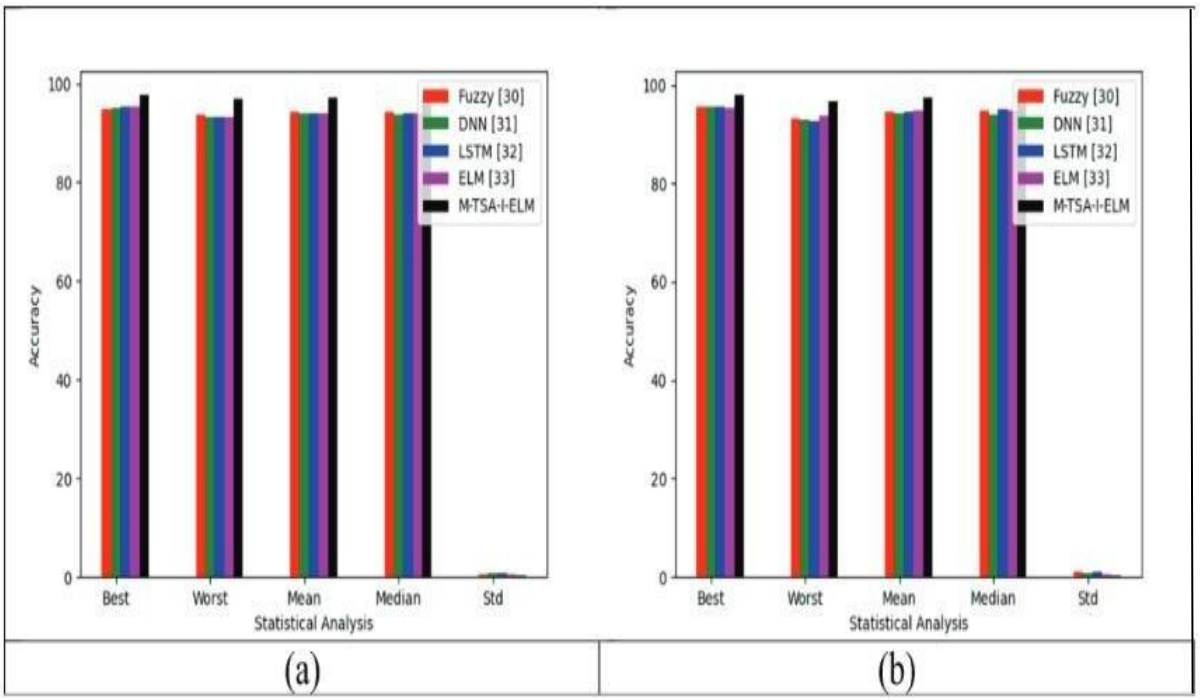

Figure 3.4:Statical analysis of proposed epileptic seizure detection model with different classifiers for (a) dataset1 (b) dataset 2.

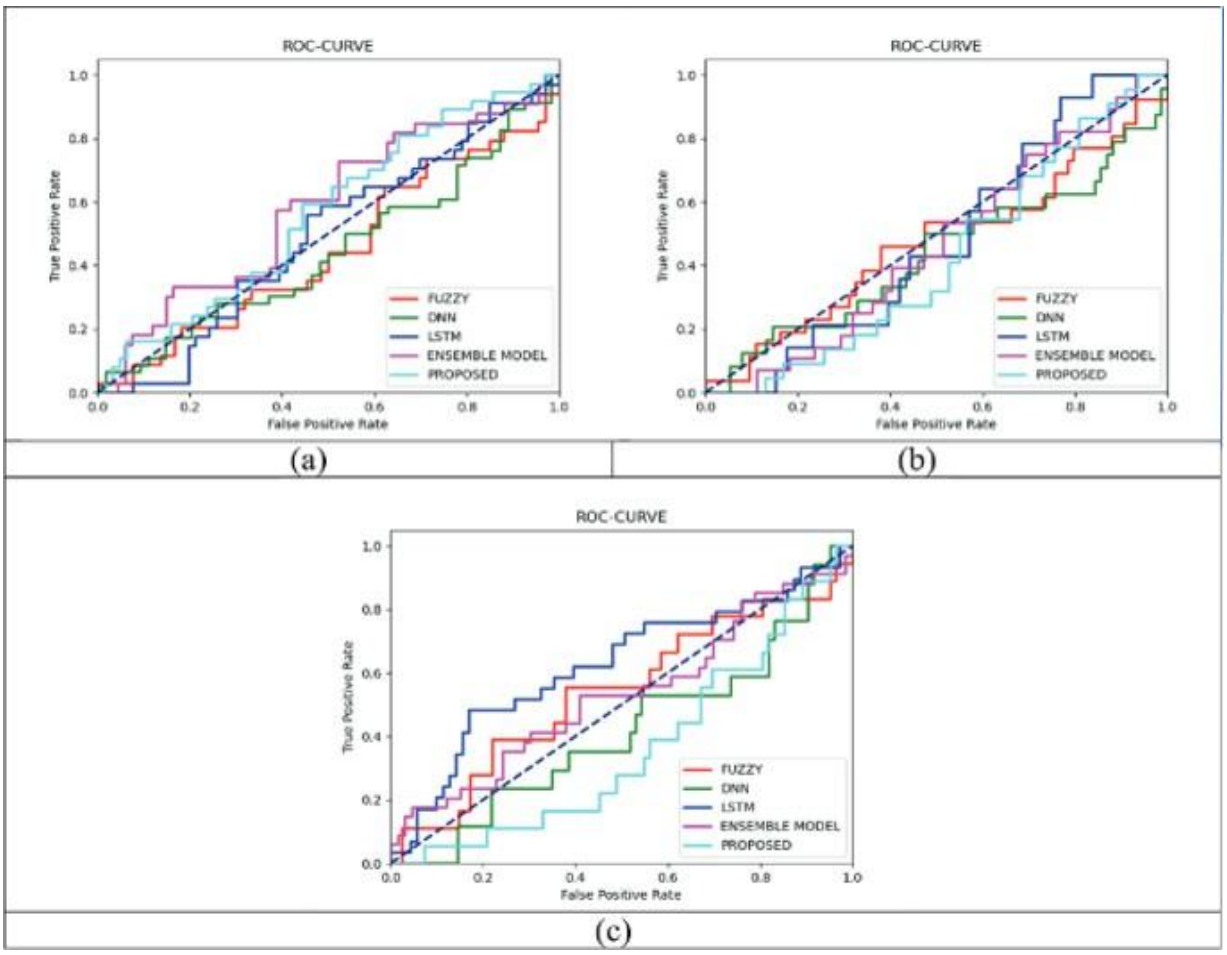

Figure 3.5 ROC plots for the proposed FS-SSO-Yolo model with various deep learning model1(b) dataset 2 (c) dataset 3.

3.3.7 Comprehensive evaluation of the epileptic EEG dataset's performance

The comprehensive evaluation of the proposed epileptic seizure identification technique using a variety of current conventional methods and deep learning on the Epileptic EEG Dataset 3 presents a performance analysis on Dataset 3 for the proposed epileptic seizures detection method using different conventional algorithmic methods.

The suggested M- TSA-I-ELM technique is obtained to be 3.15%, 6.68%, 3.10%, and 2.99% better than PSO-I-ELM, GWO-I-ELM, WOA-I-ELM, and TSA-I-ELM, respectively, from 3.6 in terms of accuracy. Similarly, the proposed M-TSA-I-ELM technique achieves 25.69%, 12.79%, 32.41%, and 34.52% enrichens in terms of FPR compared to LSTM, DNN, ELM, and fuzzy, respectively. Therefore, it has been demonstrated that, for dataset 3, the suggested M-TSA-I-ELM approach is more enriched than the other traditional deep learning methods.

Table 3.6 shows an overall performance study of the epileptic seizures detection model with various algorithms and classifiers on Dataset 3.

Dataset 2					
Algorithms	PSO-I-ELM (Ahmed et al. 2020)	GWO-I-ELM (Nagal et al. 2019)	WOA-I-ELM (Dingli et al. 2020	TSA-I-ELM (Kaur et al. 2020)	PROPOSED M-TSA-I-ELM
Accuracy	0. 956533	0. 955733	0. 952533	0.9616	0. 96877
Sensitivity	0. 975289	0. 975328	0. 971467	0. 980552	0. 987849
Specificity	0. 502946	0. 490773	0. 502634	0. 509207	0. 502691
Precision	0. 979364	0. 97847	0. 978903	0. 97946	0. 97981
FPR	0. 497054	0. 509227	0. 497366	0. 490793	0. 497309
FNR	0.024711	0.024672	0.028533	0.019448	0.012151
NPV	0. 502946	0. 490773	0. 502634	0. 509207	0. 502691
FDR	0.020636	0.02153	0.021097	0.02054	0.02019
F1-score	0. 977306	0.02153	0. 975167	0. 979995	0. 983812
MCC	0. 462874	0. 450022	0. 439316	0. 501979	0. 546631

3.4 Summary. The disadvantages of the existing traditional algorithms are given by the premature convergence of PSO is low. GWO can be producing multi-class classification issues. The computations time of WOA is more and tedious. For TSA, poor exploitation and premature convergence are the main problems for the optimization algorithms. Accordingly, the challenges of deep learning algorithms are depicted below, DNN suffers large-scale optimization issues. I-ELM needs to combine more heterogeneous data sources for the classification model. Fuzzy will easily fall into the local optimum. LSTM holds only a few for detecting epileptic seizures using EEG signals and needs more efficiency to enhance the accuracy of classification method

Chapter 4

A New Design of Epileptic Seizure Detection Using Hybrid Heuristic-Based Weighted Feature Selection and Ensemble Learning

4.1 Introduction

The diagnosis of the neurological disorder traditionally relies on manual interpretation and visual inspection of EEG signals. While recent advancements in deep learning have addressed the complexity of this issue through end-to-end learning, existing models have yet to fully harness the potential of EEG data for the detection of seizures. This chapter aims to introduce a novel approach to detecting seizures in EEG signals by employing innovative categorization and feature extraction methods. The initial phase of the suggested model involves signal pre-processing. Subsequently, a combination of DWT and EMD is applied for signal decomposition. This dual technique enhances the efficiency of the analysis, paving the way for more accurate and robust seizure detection in EEG data. After the signal decomposition process, the proposed model continues by performing feature selection through the concatenation of LDA and PCA. This selected set of features undergoes further refinement through a weighted feature selection approach, where the optimizing the weight using the J-CSO hybrid meta-heuristic algorithm. Notably, J-CSO boasts ease of implementation and lacks dependence on algorithm-specific parameters, making it highly applicable to optimization issues in the real world. Capitalizing on these benefits, the efficiency of the recommended model surpasses that of conventional approaches. In the subsequent detection phase, an I-ELM is discovered, utilizing the J-CSO-based heuristics. This model incorporates three distinct classifiers: a DNN, LSTM and a fuzzy classifier network. The achieved accuracy is comparable to contemporary seizure categorization methods, positioning this approach as a potent tool for medical practitioners to efficiently analyze large datasets and expedite the process of seizure diagnosis.

4.2 Proposed Methodology

4.2.1 Dataset Details

The recommended model for detection of epileptic seizure has acquired input signals from the EEG from two distinct datasets: "GitHub and Physio Net.".

Dataset 1: The signals of the EEGused as input are sourced from "https://physionet.org/content/chbmit/1.0.0/" with an access date of November 16, 2023. The dataset, provided by "Children's Hospital Boston," comprises EEG seizure recordings from 22 epileptic patients. Within this dataset, there are recordings from 12 female patients and 5 male patients, ranging in age from 1.5 to 19 for females and 3 to 22 for men. The dataset produces 198 raw EEG signals in total, which our algorithm cn analyze.
Dataset 2: The EEG signals utilized as input are sourced from "https://github.com/akshayg056/Epileptic-seizure-detection" with an access date of November 16, 2023. Dataset 2 encompasses EEG recordings from 500 individuals, each containing 4097 data points. In this context, each data point represents the EEG recording values over a duration of 23.6 seconds. For epileptic seizure detection, only the first column is utilized, while the remaining four columns are employed to detect other medical conditions.

The gathered input signals of EEG are specified as KL_t, where $t = 1,2,...,T$ and the input of total signal is expressed as G.

To assess the effectiveness of the recommended method, a comprehensive validation approach incorporates two datasets, namely Dataset 1 and 2. Dataset 1 comprises a total of 198 input signals of EEG, while Dataset 2 encompasses EEG recordings from 500 individuals, each containing 4097 data points. This multi-dataset strategy allows for a more robust evaluation of the recommended method's performance. The selection of diverse datasets is crucial to ensure that the suggested method's efficiency is not merely validated on similar specimens, thereby enhancing the generalizability and credibility of the evaluation process [132].

4.2.2 Recommended I-ELM-based Detection

The recommended method for detection of epileptic seizure introduces an innovative I-ELM which incorporates three classifiers—namely, DNN, LSTM, and fuzzy classifiers. These classifiers are employed in conjunction with the recommended J-CSO method. The chosen weighted features undergo classification within the suggested I-ELM to detect EEG signals indicative of non-epileptic or epileptic seizure events. The ensemble-based detection of seizures approach enhances the overall efficiency of the suggested detection of epileptic seizure systems. This improvement is achieved through accurate prediction and classification, leveraging the consensus among the outcomes provided by the three classifiers. The recommended J-CSO finds the ideal number of

concealed neurons for each of the LSTM and DNN classifiers and additionally improves the membership bounds of the fuzz classifier. The optimized procedure plays a key role in improving the system's overall effectiveness in classification.

Fuzzy Classifier [93 The Fuzzy classifier leverages the principles of fuzzy set theory to effectively handle and compute ambiguity and uncertainty. To enhance its performance, the fuzzy classifier optimizes the membership functions.

DNN Classifiers [94]: The DNN classifier within the suggested I-ELM is designed to achieve precise classification through the utilization of optimal input feature. To enhance the efficiency of the DNN classifier, the suggested J-CSO is employed to optimize its hidden neurons. linked to the output layer and hidden layer. The DNN result finds either the EEG signals include seizures that are not epilepsy or epilepsy.

LSTM Classifiers [125]: The recommended model for detection of epileptic seizure incorporates the I-ELM with the introduced J-CSO. Within this framework, the classifier of LSTM is utilized to classify optimal features for the detection of epileptic seizures in EEG signals. The network LSTM retains the output from the last layer, facilitating effective seizure detection. "Input gate, cells, forget gate, and output gate" are the four parts of the LSTM system. Data must be randomly transferred between both output and input gates by the network's cell. The output is then computed by the network formed by the LSTM

Through the recommended J-CSO, hidden neurons are optimized, further refining the LSTM classification. As a result, based on ideal characteristics, the LSTM classification differentiates between different EEG data having non-epileptic or epileptic occurrences. Figure 5.1 shows the proposed I-ELM for categorization within the proposed irregular seizures recognition model.

In conclusion, the outcome from the three classifiers is collectively assessed to identify epileptic seizures in EEG signals [134]. The output that has the highest score is considered the final outcome for the suggested epileptic seizure identification system. This approach ensures that the accurate classification of epileptic seizures is achieved by prioritizing the high-ranking output over the three classifiers

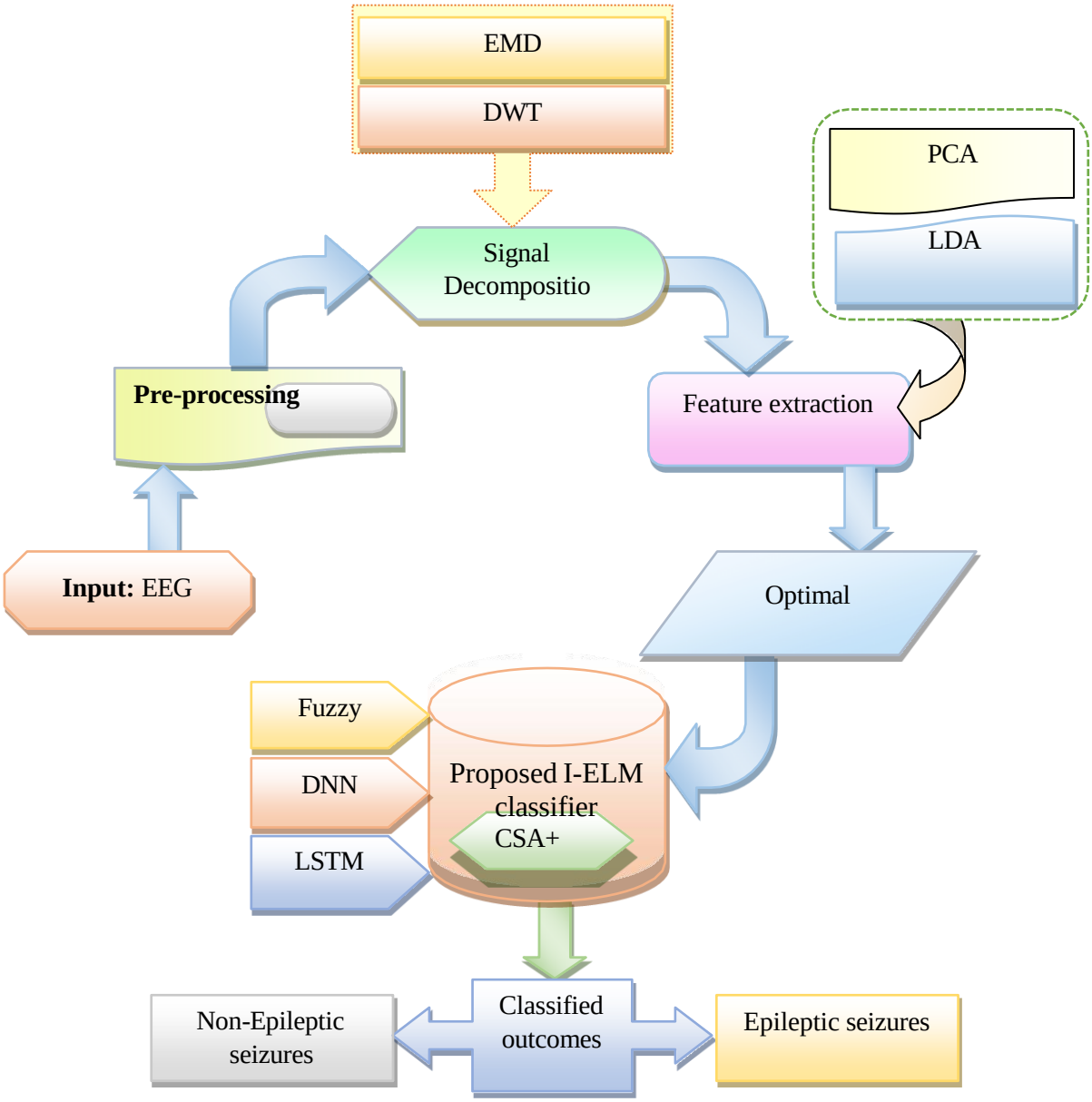

Figure 4.1: Classification of I-ELM-based seizure

4.2.3 Proposed Elliptic Seizure Detection Models Objective Function

The enhanced classification of epileptic seizure, as suggested in the context of I-ELM, exhibits improved detection efficiency through the meticulous selection of optimal weighted features. This enhancement is made possible by applying the novel J-CSO technique to optimize the membership function of both Fuzzy and hidden neurons within the corresponding LSTM and DNN classifiers. The suggested model's main focus is on a multiple objectives function, with the explicit goal of maximizing detecting seizures precision and accuracy.

The suggested J-CSO approach is employed to determine these optimal weights, with a total of 10 features being selected.

Additionally, the J-CSO algorithm is utilized to optimize the bounding parameters within the Fuzzy system, restricting them to the interval of 0.1 to 0.9. Similarly, the hidden neurons for both the LSTM and DNN classifiers are fine-tuned within specified ranges. The accuracy, denoted as AcT , is defined as the "closeness of the measurements to a specific value," as outlined in Eq. (4.1).

$$acr = \frac{\left(U_p + U_n\right)}{\left(U_p + U_n + I_p + I_n\right)} \tag{4.1}$$

Precision denoted as ppr and is elucidated as "the fraction of relevant instances among the retrieved instances," as expressed in Eq.(4.2).

$$ppr = \frac{U_p}{U_p + I_p} \tag{4.2}$$

In this context, U_p and U_n refers to the true positive value and negative value. Similarly, I_n signifies the false negative value, and I_p corresponds to the false positive value. The encoding solution for the suggested detection model of epileptic is illustrated in Figure 5.2.

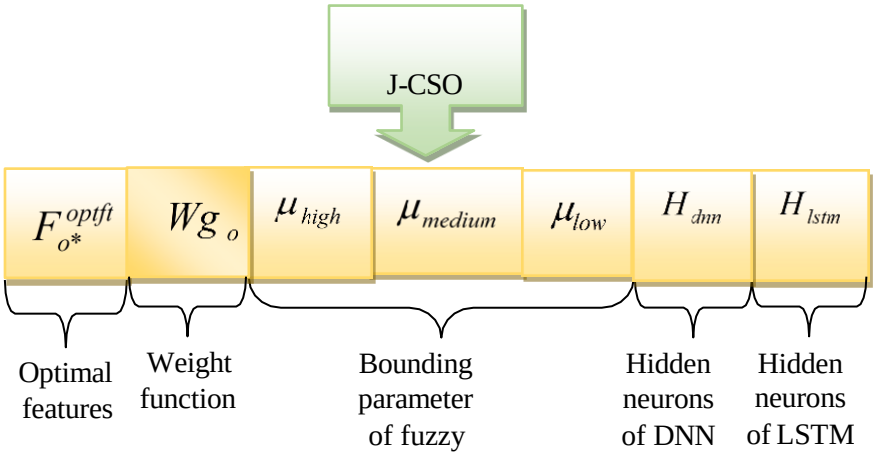

Figure 4.2: Suggested model's solution encoding view

4.2.4 Optimization of Jaya-Cat Swarm for Selection of Optimal Feature in the Detection of Epileptic Seizures

4.2.4.1 Description of Architecture

Epilepsy stands out as a severe disorder of neurology characterized by the sudden onset of seizures. The underlying causes of seizures in epileptic patients remain unidentified, making epilepsy a condition that can manifest anywhere in the world. Consequently, the detection of epilepsy poses a complex challenge. EEG emerges as a valuable method for diagnosing epilepsy, offering an efficient means to discern differences in brain activity during various states of epilepsy. Neurologists can differentiate between epileptic brain and normal activities, both in the interictal (between seizures) and ictal (seizure) states, based on recorded EEG signals. To streamline the detection process, numerous research efforts have implemented automatic models for epileptic seizure detection. These models aim to mitigate the time-consuming nature of manual assessments, which require extensive EEG [133] recordings and can lead to inaccuracies. Although deep learning approaches have gained attention for automatic seizure detection, their efficacy is hindered by suboptimal classifier design and inadequate representation of time-domain signals. Various categorization procedures have been used to classify seizures with epilepsy classes utilizing deep learning techniques such as ―ANN, CNN, SVM‖ , and wavelet neural networks. Traditional detection of seizure methods often involves manual analysis, contributing to inefficiencies in efficiency. In light of these challenges, a novel model for epileptic detection of seizure is suggested, leveraging deep learning techniques, as illustrated in Figure 5.3.

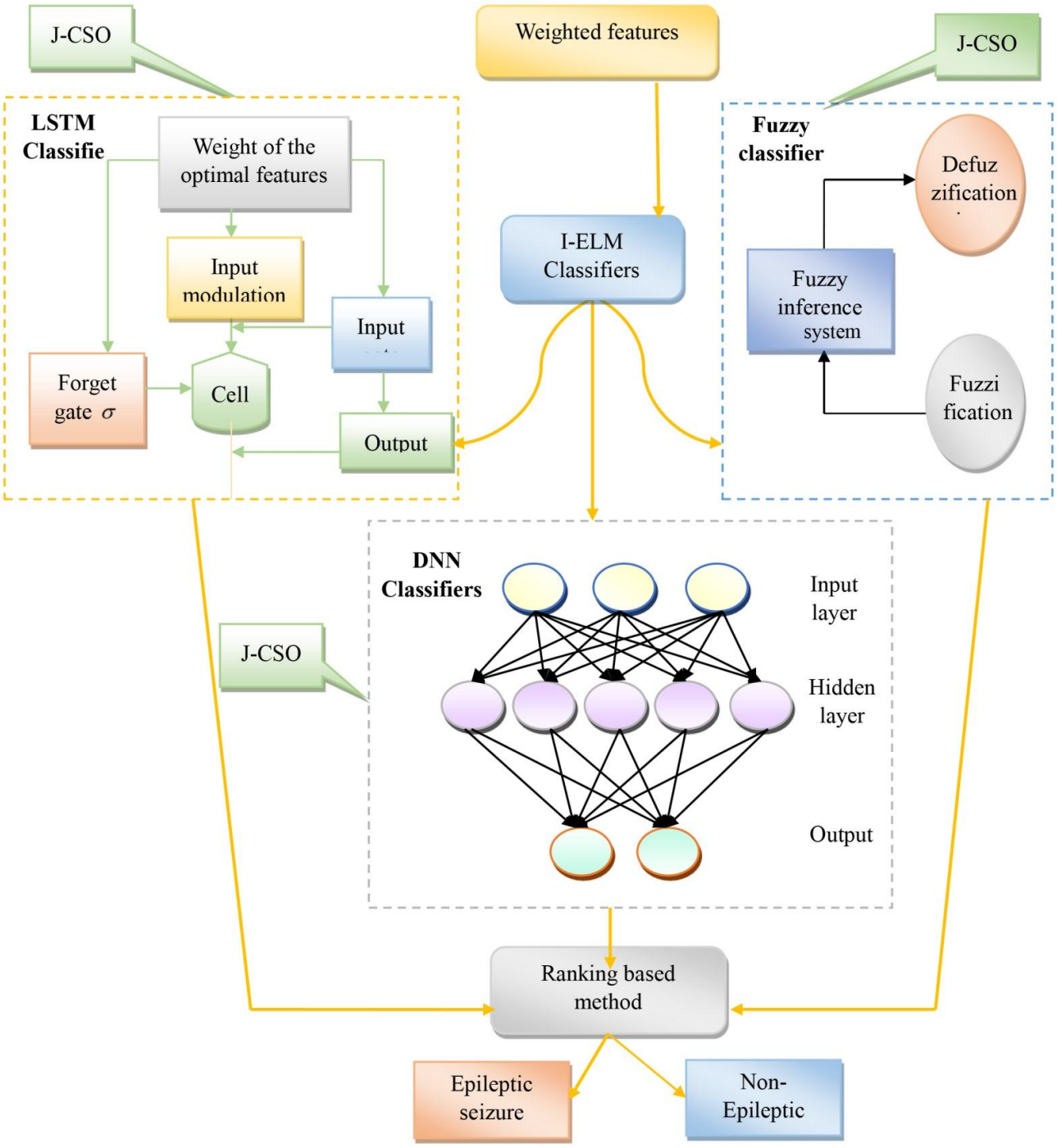

Figure 4.3: Suggested detection of epileptic seizure model utilizing deep learning

The suggested model consists of five sequential phases: "signal decomposition, pre-processing, optimal feature selection, feature extraction, and ensemble learning-based detection." First, amplitude-modulated spectroscopy is utilized to pre-process the input EEG data using the STFT technique in order to remove artifacts and distortion. After that,

the pre-processed electrical brainwaves are subjected to signal breakdown using DWT and EMD separately. This produces a series of EEG signals at various continuous frequencies. The broken-down signals using DWT and EMD [129] are combined for use in the next stage of feature extraction. As with signal decomposition, two different approaches—LDA and PCA—are used independently throughout the feature extraction phase. A single set of characteristics is created by concatenating the resultant characteristics obtained from the two methods. After the extraction of characteristics, the retrieved features go through an optimal feature choice phase, where the best features are selected by using the recommended J-CSO to optimize weight functions. The chosen characteristics are subjected to training and detection using the DNN-developed I-ELM classifier, as well as LSTM and classifiers for the identification of seizures. The same J-CSO is employed in the detection of seizure. The overarching objective in the suggested detection model of epileptic seizure is a multi-objective function that aims to enhance precision and accuracy by membership limits of hidden neurons and Fuzzy in the LSTM and DNN utilizing the developed J-CSO. Finally, the categorization is carried out by taking into account the highest-ranking findings from the I-ELM classifier's categorized results in order to ascertain whether signals from an EEG are suggestive of non-epileptic or epileptic seizures.

4.2.4.2 Suggested J-CSO

To improve the efficacy of the recommended seizure model identification, the CSO and JA are integrated to form the J-CSO meta-heuristic technique. By using J-CSO, the weight functional is improved and ideal features are chosen, which improves the performance of the model's LSTM and DNN classifiers. The inclusion of J-CSO results in improved accuracy in the detection of epileptic seizure. The choice of CSO [126] in this recommended model is motivated by its rapid convergence and effective balancing of the ―exploitation and exploration phases."

On the other hand, the CSO method is prone to the issue of entering local optima, which might lead to an initial convergence difficulty. In order to get over these constraints, a novel meta-heuristic technique called J-CSO is put into practice by incorporating JA traits into the CSO algorithms. JA functions using standard variables, which means that it does not require any control variables specific to the method. The existing system is updated by employing the recommended J-CSO technique. When a solution is in seeking mode, the CSO algorithm in seeking mode is utilized for updates. Alternatively, if the solution is not in the seeking mode, the update is performed using the JA-based approach rather than

relying on the tracing mode of the CSO algorithm. This strategy proves effective in addressing challenges related to premature local optima and convergence during the process of optimization.

CSO [126] draws inspiration from the tracing and resting behaviors exhibited by cats. Although cats are generally perceived as lazy creatures, it is crucial to recognize that they remain vigilant of their surroundings even during periods of rest. When cats identify a target in their vicinity, they exhibit sudden, purposeful movement towards that target. Consequently, CSO is designed around two distinct modes of cats: tracing and seeking. In the suggested J-CSO, a departure from the CSO algorithm is made by exclusively considering the seeking mode for solution updates. Notably, the tracing mode is substituted with the JA for updating solutions in J-CSO. Unlike CSO, which employs both seeking and tracing modes, the proposed J-CSO focuses solely on the seeking mode for enhancing solution updates. Each cat in the CSO algorithm is defined by a solution set encompassing its fitness position, flag, and value. The solution set's location, represented in a multidimensional space, is accompanied by its unique velocity during exploration. The value of fitness serves as a metric indicating the efficacy of the solution set, while the flag guides the solution set in transitioning between tracing and seeking modes. At first, the cats or solution sets are characterized by their respective upper and lower bounds. Subsequently, the population of cats is randomly dispersed across the dimensions within the search space. To initiate the tracing and seeking modes, the cats are randomly assigned to these modes based on the MR, facilitating an arbitrary division of the population between the two modes.

The MR value for the cats ranges between 0 and 1. For instance, when the population consists of 10 cats, an MR value of 0.2 indicates that 2 cats are assigned to the tracing mode, while the remaining 8 cats are allocated to the seeking mode. Then, each kitten's fitness value is determined, and the top-performing cat is stored in memory. Answer sets go through both tracing and searching modes throughout this iterative process, and their efficacy values are computed to keep the most advantageous sets in place until the halting condition is satisfied. Solution sets are repeatedly run through the JA-based inform or searching mode in the recommended J-CSO.

Seeking mode: The mode of seeking is grounded in the resting character of solution sets and contains four fundamental variables: SRD, SMP, SPC, and CDC." In this context, SMP denotes the location of cats, where new locations are allocated, and a solution set is selected as the next location of the cat, assisted by CDC and SRD. The number of

parameters that must be changed is specifically determined by the CDC, and it must fall between 0 and 1.

In this process, only the optimal solutions are taken into account for updating the location, while the suboptimal solutions are disregarded. This iterative update of solutions culminates in the determination of the overall optimal solution. The pseudo code outlining the suggested J-CSO is presented in Algorithm 5.1.

Algorithm 5.1: Recommended J-CSO

Population initialization with a user-defined number of sets of solutions and iterate over the specified number of generations. NU_{itn}

Determine the fitness for every set of solution

Arrange the solution sets in the population based on their fitness values, with higher fitness values coming first.

Determine the amount of active solution sets based on their values of high fitness.

Choose the better solution set with fitness of high

Assume $uy = 0$

Consider recent solution set $YT_{itn} = 0$

While $(UY < YT_{itn})$

While $(YT_{itn} < NG_{active})$

If (is in mode of seeking)

Optimize the location using Eq. (21)

Else

Optimize the location using Eq. (22)

End

Optimize every solution set until the criterion is stopping.

Return the best solution set obtained during the optimization process.

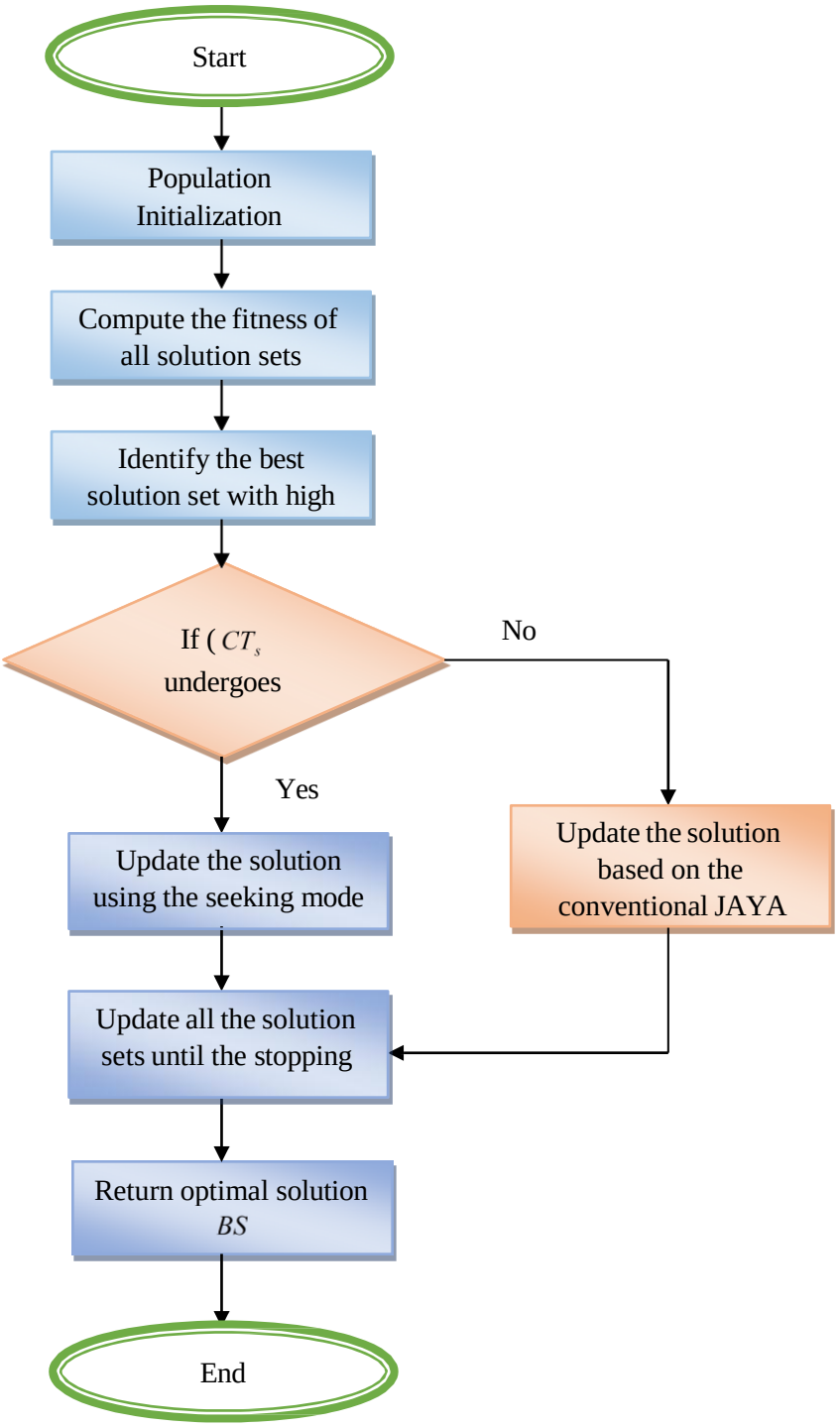
Start
Population Initialization
Compute the fitness of all solution sets
Identify the best solution set with high
If (CT_s undergoes
No
Yes
Update the solution using the seeking mode
Update the solution based on the conventional JAYA
Update all the solution sets until the stopping
Return optimal solution BS
End

Figure 4.4 Recommended J-CSO algorithm's flowchart is represented diagrammatically.

4.2.5 Optimal selection of feature and Feature extraction for detection of elliptic seizure

4.2.5.1 Pre-processing Signal

This approach seeks to eliminate unnecessary artifacts and mitigate noise. Through time-frequency analysis, the pre-processing stage combines the frequency domain and temporal representations of the signal, generating a time-frequency energy density function. This technique is widely used for detecting and estimating epileptic seizures. STFT [128] is acknowledged for its linear frequency of time analysis capabilities, transforming input signals of the EEG into images of time-frequency. The method provided amplitudes of complex signals, offering localized frequency and time data essential for understanding non-stationary signals.

4.2.5.2 Decomposition of Signal

The recommended approach for the epileptic seizure detection involves signal decomposition, utilizing preprocessed EEG signals FG_g^{presig}. The signal is decomposed and separated into distinct components based on frequency bands, employing both EMD and DWT techniques. These decomposition methods significantly improve the efficiency of automatic detection of seizure.

4.2.5.3 Selection of Optimal Weighted Feature using suggested J-CSO

In the suggested detection model of epileptic seizure, employ a selection of weighted feature approach to find the optimal subset of features among the extracted set FG_g^{presig}. This selection is guided by the minimization of feature length, aiming to enhance the efficiency of the model. The weights assigned to the features extraction are optimized through the suggested J-CSO method. The goal is to enhance efficiency of detection by simultaneously lowering the complexity of training.

4.3 RESULTS AND DISCUSSIONS

4.3.1 Experimental setup

The proposed epileptic seizure detection model was implemented in python, and experimental analysis was carried out. The performance of the proposed model was evaluated by comparing with the conventional methods using different quantitative measures. These quantitative measures were divided into two classes as positive and negative measures. ―Positive measures or Type I includes Negative Predictive Value

(NPV), Specificity, Accuracy, MCC, Precision, Sensitivity, and F1Score. Negative measures were taken as Type II measures such as False Discovery Rate (FDR), False Negative Rate (FNR) and False Positive Rate (FPR)‖ . The experimental analysis was carried out under the number of population as 10 and maximum number of iterations as 25 in the proposed epileptic seizure detection model. The proposed J-CSO was compared with other meta-heuristic algorithms like ―Tunicate Swarm Algorithm (TSA) [36], Modified Tunicate Swarm Algorithm (M-TSA) [39], CSO [26], Jaya [27] and machine learning algorithms like Fuzzy [33], Deep Neural Network (DNN) [34], Long Short-Term Memory (LSTM) [35], ELM [38], M-TSA-I-ELM [39]‖ .

4.3.2 Performance metrics

The performance of proposed epileptic seizure detection model are tested to verify the quality of the developed model using various quantitative measures that are described as follows

(a) MCC M_{cc} is ―a measure of the quality of binary classifications of testing as given in the Eq. (4.3)

$$M_{cc} = \frac{tt_p \times tt_n - fl_p \times fl_n}{\sqrt{(tt_p + fl_p)(tt_p + fl_n)(tt_n + fl_p)(tt_n + fl_n)}} \tag{4.3}$$

(b) Specificity S_{spcty} is ―the proportion of negatives that are correctly identified as represented in the Eq. (4.4)

$$S_{spcty} = \frac{tt_N}{tt_N + fl_p} \tag{4.4}$$

(c) NPV N_{pv} is described as ―the sum of all persons without disease in testing as denoted in Eq. (4,5)

$$N_{pv} = \frac{tt_n}{tt_n + fl_n} \tag{4.5}$$

(d) F1-score F_{score} is determined as ―the measurement of the accuracy in the conducted test‖ as given in Eq. (4.6)

$$F_{score} = 2 \times \frac{2tt_P}{2tt_p + fl_p + fl_n} \tag{4.6}$$

(e) FNR F_{nr} is ―the proportion of positives which yield negative test outcomes with the test‖ as given in Eq. (4.7)

$$F_{nr} = \frac{fl_n}{fl_n + tt_p} \tag{4.7}$$

(g) Sensitivity $S_{senstvy}$ is ―the proportion of positives that are correctly identified as denoted in Eq. (4.8)

$$S_{senstvy} = \frac{tt_p}{tt_p + fl_n} \tag{4.8}$$

(h) FPR F_{pr} is defined as ―the ratio between the numbers of negative events wrongly categorized as positive (false positives) and the total number of actual negative events as given in Eq. (4.9)

$$F_{pr} = \frac{fl_p}{fl_p + tt_n} \tag{4.9}$$

(i) FDR is ―a method of conceptualizing the rate of errors in testing when conducting multiple comparisons, as denoted in Eq. (4.10)

$$F_{dr} = \frac{fl_p}{fl_p + tt_p} \tag{4.10}$$

4.3.3 Performance analysis on weighted feature selection for dataset 1 and dataset 2

The performance of the weighted features selection process in the proposed epileptic seizure detection with dataset1 and dataset 2 is evaluated by comparing with feature selection and without feature selection process using various quantitative measures. The weighted feature selection process improves the overall performance of the proposed epileptic seizure detection. The accuracy of the proposed J-CSO-I-ELM is 25% better than without optimal weighted feature selection in the dataset 1. Similarly, the proposed J-CSO-I-ELM gives 12.5% higher accuracy than without weighted feature selection in the dataset 2. From this comparison, it is seen that the negative error measures were decreased in the proposed J-CSO-I-ELM with optimal weighted feature selection. Therefore, the performance of the proposed model with optimal weighted feature selection is superior to the conventional models without weighted feature selection models, which is observed in both the dataset 1 and dataset 2.

4.3.4 Performance analysis on dataset 1

The performance of the proposed epileptic seizure detection is validated based on the dataset 1 by comparing with different meta-heuristic algorithm and various classifiers that is given respectively at varying the learning percentages. By considering the F1-score of the proposed J-CSO-I-ELM, the performance is 0.4%, 0.35%, 0.37% and 0.37% improved than the TSA-I-ELM, M-TSA-I-ELM, CSA-I-E LM and JA-I-ELM, respectively at the learning percentage of 85. The accuracy of the proposed model is compared with different

classifiers, which gives 6.45%, 6.45%, 7.6%, 8.79%, and 0.2% correspondingly enhanced performance than the Fuzzy, DNN, LSTM, ELM, and M-TSA-I-ELM at the learning percentage of 65. While observing the sensitivity performance, the proposed model suddenly increases at the learning percentage of 50, which maintains the value of 99.4 at most of the learning percentage and at last, reaches the higher sensitivity value on changing the learning percentages. Similarly, for all the performance measures, the proposed J-CSO-I-ELM outperforms in terms of epileptic seizure detection model the conventional methods for dataset 1

4.3.5 Performance analysis on dataset 2

The performance of the proposed epileptic seizure detection based on the dataset 2 is tested with different meta-heuristic algorithm and various classifiers respectively at varying the learning percentages. The performance of the proposed J-CSO-I-ELM provides 0.2%, 1.17%, 0.72% and 0.3% higher accuracy than the TSA-I-ELM, M-TSA-I-ELM, CSA-I-ELM and JA-I-ELM, respectively at the learning percentage of 65. The F1-score of the proposed model is maintained at the high value among all value is maintained at all learning percentage with the slight variation. The performance of proposed J-CSO-I-ELM shows 2.06%, 2.06%, 2.06%, 2.06% and 1.02% better precision than the Fuzzy, DNN, LSTM, ELM and M-TSA-I-ELM, respectively at the learning percentage of 55. Here, the proposed J-CSO-I-ELM model drastically decreased all the errors in terms of negative measures when compared to the conventional classifier methods at every learning percentage. Thus, the proposed epileptic seizure detection model with dataset 2 provides enhanced performance than the existing methods other meta-heuristic algorithms, in which it shows the constant F1-score

4.3.6 Overall Performance analysis of the proposed epileptic seizure detection model for dataset 1

The proposed epileptic seizure detection model is compared with various meta-heuristic algorithms and classifiers, which is correspondingly shown in the Table I and Table II for Evaluating its performance based on the dataset 1. The comparison between the proposed and other algorithms indicates the enhanced performance of the proposed J-CSO-I-ELM by decreasing the errors that affect the detection performance. The performance of the proposed J-CSO-I-ELM is 5.27%, 0.06%, 3% and 3.68% correspondingly improved in MCC value than the TSA-I-ELM, M-TSA-I-ELM, CSA-I-ELM and JA-I-ELM. The

developed J-CSO-I-ELM shows the superior performance regarding accuracy, in which it gives 4.76%, 0.6%, 4.13%, 2.11% and 4.22% higher value while comparing with the Fuzzy, DNN, LSTM, ELM, M-TSA-I-ELM, respectively. Therefore, the proposed epileptic seizure detection model enhanced its performance among all other existing methods on

Table 4.1. Comparative Analysis on Epileptic Seizure Detection Model with dataset 1 based on Existing Meta- Heuristic Algorithm dataset 1

Algorithms	TSA-I-ELM [36]	M-TSA-I-ELM [39]	CSO-I-ELM [26]	JA-I-ELM [27]	J-CSO-I-ELM
Accuracy	0.973215	0.97523	0.97363	0.973511	0.975644
Sensitivity	0.991569	0.993597	0.992056	0.991873	0.993847
Specificity	0.496	0.503165	0.503145	0.501582	0.5
Precision	0.980825	0.980915	0.980762	0.980823	0.98111
FPR	0.504	0.496835	0.496855	0.498418	0.5
FNR	0.008431	0.006403	0.007944	0.008127	0.006153
NPV	0.496	0.503165	0.503145	0.501582	0.5
FDR	0.019175	0.019085	0.019238	0.019177	0.01889
F1-score	0.986168	0.987216	0.986377	0.986317	0.987438
MCC	0.573399	0.604034	0.586004	0.582171	0.603623

Table 4.2. Comparative Analysis on Epileptic Seizure Detection Model with dataset 1 based

on Existing Classifier

Classifiers	Fuzzy [33]	DNN [34]	LSTM [35]	ELM [38]	M-TSA-I-ELM [39]	J-CSO-I-ELM
Accuracy	0.931259	0.969659	0.936889	0.955437	0.936059	0.975644
Sensitivity	0.966902	0.9892	0.972692	0.992115	0.971039	0.993847
Specificity	0.498833	0.498512	0.498824	0.507053	0.505521	0.5
Precision	0.959028	0.979407	0.95959	0.960944	0.960271	0.98111
FPR	0.501167	0.501488	0.501176	0.492947	0.494479	0.5
FNR	0.033098	0.0108	0.027308	0.007885	0.028961	0.006153
NPV	0.498833	0.498512	0.498824	0.507053	0.505521	0.5
FDR	0.040972	0.020593	0.04041	0.039056	0.039729	0.01889
F1-score	0.962949	0.984279	0.966097	0.976281	0.965625	0.987438
MCC	0.488819	0.55706	0.51315	0.632404	0.51044	0.603623

4.3.7 Overall Performance analysis of the proposed epileptic seizure detection model for dataset 2

The overall performance analysis is made on the proposed epileptic seizure detection model for estimating its performance on the dataset 2 among various meta-heuristic algorithms and different classifiers that is correspondingly portrayed in the Table VII and Table VIII. By considering the sensitivity of the proposed J-CSO-I-ELM, the performance enhances 0.42%, 0.12%, 0.34% and 0.38% than the TSA-I-ELM, M-TSA-I-

ELM, CSA-I-ELM and JA-I-ELM, respectively. The proposed J-CSO-I-E LM based on the MCC value gives 5.81%, 15.7%, 19.4%, 14.8% and 31.09% correspondingly better performance than the Fuzzy, DNN, LSTM, ELM, M-TSA-I-ELM. The proposed J-CSO-I-ELM provides a higher value in the positive measures and lower value in the negative measures, which shows the performance of proposed model based on various quantitative measures with dataset 2. Therefore, the proposed epileptic seizure detection model with dataset 2 enhances its performance that the existent methods.

Table 4.3. Comparative Analysis on Epileptic Seizure Detection Model with dataset 2 based on Existing Meta- Heuristic Algorithm

Algorithms	TSA-I-ELM [36]	M-TSA-I-ELM [39]	CSO-I-ELM [26]	JA-I-ELM [27]	J-CSO-I-ELM
Accuracy	0.972859	0.975467	0.973511	0.973215	0.976652
Sensitivity	0.991077	0.994089	0.991934	0.991506	0.995322
Specificity	0.4992	0.49763	0.50079	0.5	0.495238
Precision	0.980936	0.980685	0.980763	0.98088	0.980712
FPR	0.5008	0.50237	0.49921	0.5	0.504762
FNR	0.008923	0.005911	0.008066	0.008494	0.004678
NPV	0.4992	0.49763	0.50079	0.5	0.495238
FDR	0.019064	0.019315	0.019237	0.01912	0.019288
F1-score	0.98598	0.987342	0.986317	0.986165	0.987963
MCC	0.570414	0.606109	0.582381	0.576235	0.620491

Table 4.4. Comparative Analysis on Epileptic Seizure Detection Model with dataset 2 basedon Existing Classifier

Algorithms	Fuzzy [33]	DNN [34]	LSTM [35]	ELM [38]	M-TSA-I-ELM [39]	J-CSO-I-ELM
Accuracy ‖	0.949037	0.967881	0.937778	0.941156	0.928178	0.976652
Sensitivity	0.985381	0.986498	0.973959	0.976786	0.963889	0.995322
Specificity	0.505864	0.50687	0.498442	0.507416	0.494548	0.495238
Precision	0.9605	0.980213	0.959315	0.960222	0.958602	0.980712
FPR	0.494136	0.49313	0.501558	0.492584	0.505452	0.504762
FNR	0.014619	0.013502	0.026041	0.023214	0.036111	0.004678
NPV	0.505864	0.50687	0.498442	0.507416	0.494548	0.495238
FDR	0.0395	0.019787	0.040685	0.039778	0.041398	0.019288
F1-score	0.972781	0.983346	0.966582	0.968433	0.961238	0.987963
MCC	0.586376	0.536202	0.519444	0.540128	0.473304	0.620491

4.4 Computational time

The CSO has a computational complexity of M × (CS × D). The JA has a computational complexity of CS × D. Fig. 8 (continued) shows the computational complexity of the J-CSO. A novel approach to weighed feature-based hybrid heuristic seizure identification in epilepsy CS × D + 1 3M × (CS × D). Here, M is the maximum number of iterations and D is the number of dimensions of a solution.

4.5 Summary:

This work has proposed an epileptic seizure detection model using I-ELM. Initially, the EEG signals were pre-processed by STFT. Then, the signal decomposition was performed by DWT. The feature extraction process was carried out on the decomposed signals using the temporal and spatial feature extraction techniques. The proposed M-TSA was used for the optimal feature selection to reduce the feature-length. These optimally selected attributes were used for I-ELM detection, which has utilised three classifiers like Fuzzy classifier, DNN, and LSTM. I-ELM classifier was accomplished using the proposed M-TSA based on the high ranking, which was used to detect the seizure from the EEG signals. The performance of the proposed M-TSA-I-ELM was 2.21%, 3.38%, 4.09%, and 4.12% improved than Fuzzy, DNN, LSTM, and ELM, respectively, in terms of accuracy while considering dataset 1.

CHAPTER 5
COMPARATIVE ANALYSIS

5.1 Introduction

Epilepsy is the neurological disorder, which affects a greater number of people in the world. Although, the epilepsy symptoms include the behavioural changes, muscular cramps, uncommon sensation, unconsciousness, etc. This leads to cause damage to brain. Most of the people affected by the epilepsy do not have any seizure and can live the normal life. This is because of predicting the chances of seizure in the patients before it occurs. For diagnosing and monitoring the epilepsy, one of the efficient models is EEG, which has maximum temporal resolution at reasonable value. This model plays under the principle of several channels of the EEG signal that e5valuate the electrical activity of brain by positioning some electrodes at multiple places in brain. The electrical activity of the neuron recorded by the EEG which are the hardest biomedical signals. This leads the difficult situation in the manual investigation. However, the random and dynamic chances distribution quality of the EEG signals makes it difficult process to detect the seizure effectively in the patients with the use of EEG signals.

The novel epileptic seizure identification is proposed using the I-ELM technique. Initially, EEG signal is gathered from the benchmark database and pre-process the signal using the STFT approach. The decomposition of the signal is performed by the DWT model. Further the spatial and temporal extraction of feature helps to extract the feature from the decomposed signal. Here the M-TSA optimization is implemented to minimize the feature length to improve the functionality of the detection. The I-ELM method utilizes the selected feature to detect the epileptic seizure. Finally, the detection is performed by utilizing I-ELM with M-TSA in optimally selected feature. The identification of epileptic seizure depends on the EEG signal utilize the new feature extraction and detection model. The pre-processed EEG signal decomposed by utilizing the DWT and EMD technique. Further, the concatenation PCA and LDA select the features from the signal. The selected feature improved by implementing the weighted feature selection, here the weight is tuned by the J-CSO model. In the detection stage, I-ELM approach is used and it optimized by the J-CSO technique. The detection of epileptic seizure performed by the developed I-ELM with JCSO technique.

5.2 Comparative Analysis

Here, the comparative consequence is estimated by the two developed approach named M-TSA-I-ELM and J-CSO-I-ELM accordingly. The functionality of the model is calculated with the performance estimation in epileptic seizure detection framework.

5.2.1 Performance Estimation

To calculation of the epileptic seizure recognition using the two developed procedure based on dataset 1 and dataset 2. The approaches such as M-TSA-I-ELM and J-CSO-I-ELM are determined in this comparison by analyzing two dataset 1 and 2. From the diagrammatic representation, the J-CSO-I-ELM attains maximum accuracy when comparing it with M-TSA-I-ELM over various learning percentage. Therefore, the analysis revealed that, maximum accuracy achieved by the implemented J-CSO-I-ELM model for detecting the epileptic seizure.

5.3 Summary

This chapter observed the comparative determination of two developed framework for detecting and classifying the epileptic seizure. The techniques like M-TSA-I-ELM and J-CSO-I-ELM are determined using the performance calculation measures. When taking the accuracy value for two datasets, the J-CSO-I-ELM approach attains the maximum value. Hence the research experiment determined that the developed J-CSO-I-ELM attain the better function along with the deep learning technique.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

The suggested thesis has offered three powerful contributions for detecting epileptic seizures by employing advanced ―meta-heuristic and optimization algorithms‖ to rectify the difficulties faced in conventional seizure detection tasks. In the first contribution, the epileptic seizure was recognized by the recommended I-ELM task. At first, the EEG signals were considered from global resources, and further, they were subjected to the pre-processing state with the assistance of STFT. In addition, the DWT was supported to do the decomposition of the signal. Furthermore, by employing the Spatial and temporal‖ mechanisms, the extraction of attributes was conducted for the provided decomposed signal. To decrease the length of the attribute for maintaining the learning difficulty and improving the identification functionality, a new improved optimization mechanism called M-TSA was employed. The resultant features were subjected to the I-ELM framework that contained the LSTM and the DNN tasks. The solution of the I-ELM framework was achieved from the high-ranking task by utilizing the recommended M-TSA. In the end, the seizure-recognized solution was accomplished and contrasted with the other conventional works. When taking the second contribution, the identification of seizure was carried out with the assistance of new categorization and feature extraction mechanisms. Firstly, the obtained signals were clearly pre-processed, and further, by employing the EMD and the DWT tasks, the decomposition of the signal was carried out. Besides, the feature selection was conducted with the approach of ―weighted feature selection,‖ in that the weight was optimally tuned by the recommended J-CSO algorithms. After that, the J-CSO-aided I-ELM mechanism was used in the seizure identification process. Finally, the seizure-detected solution was obtained, and the outcomes were contrasted with the conventional seizure recognition approaches.

6.2 Major findings

The essential findings of this thesis are demonstrated as follows:

- In the first contribution, the designed task was evaluated with diverse conventional approaches to examine the efficacy of the M-TSA-I-ELM mechanism with two diverse data sources. The implemented M-TSA-I-ELM-aided mechanism's accuracy is enriched by 2.4% of TSA-I-ELM, 1.56% of WOA-I-ELM, 2.41% of GWO-I-ELM, and 1.35% of PSO-I-ELM accordingly when the learning percentage value is 65.
- In the second contribution, the recommended work was examined with various classical approaches to showcase the efficacy of the J-CSO-I-ELM-aided work. The presented work's F1-score is enhanced by 0.37% of JA-I-ELM, 0.37% of CSA-I-ELM, 0.35% of M-TSA-I-ELM, and 0.4% of TSA-I-ELM, respectively, when the learning percentage value is 85.

6.3 Future scope

The offered epileptic seizure detection approach's future scope is listed below.

- This presented work will be secured from the dimensional issues and regularized to decrease the unwanted feature selection.
- The computation and execution period of the recommended task will be diminished.
- The accuracy and quality of the implemented work will be maintained even if the given input is more.
- The presented work has to be performed well in the presence of noisy signals and replicated data.
- The uniqueness and specialty of the suggested work will be improvised.
- The designed approach should perform well in the real-time data to support the medical experts and researchers.
- The cost and the memory usage should be minimized, and this has to be considered in future work.
- The advanced deep learning tasks and the optimization tasks have to be considered for discovering the optimal solutions.
- The feature extraction methods still have to be modified and regulated for the precise outcomes.

List of publications

Paper submitted in Journal publication.

1. Vedavati Bhandari & Manjaiah D.H Improved ensemble learning model with optimal feature selection for automated epileptic seizure detection Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization https://www.tandfonline.com/loi/tciv20

2. Vedavati Bhandari1 · Manjaiah Doddaghatta Huchaiah1 A new design of epileptic seizure detection using hybrid heuristic-based weighted feature selection and ensemble learning International Journal of Intelligent Robotics and Applications https://doi.org/10.1007/s41315-022-00233-3

Paper communication.

1. Development of Enhanced Deep Learning with Optimal Temporal and Spectral feature for Epileptic Seizures Detection using Hybrid Heuristic Strategy

Papers presented National & International Conference

1.International Conference on innovation Research in Engineering and Technology on 29th and 30th September 2021organized by Institution for Engineering Research and publication (IFERP) on 29th &30th September 2021

2.7 th International Conference on Recent Trend in Engineering & Technology (ICRTET-2021 on the Title Epileptic Seizure Detection on the EEG Using the Feature Extraction on Convolution Neural NETWORK Organized by SNJB K B Jain CoE, Chandwad, Maharashtra held on 15th&16th November 2021.

3.9 th International Conference on Recent Challenges in Engineering and Technology (ICRCET-21) on 20th and 21st November Bali, Indonesia Organized by Institute For Engineering Research and Publication (IFERP) Organization.

4.Attending the 40th World Conference and Applied Science, and Technology (WCASET-2021) Organized by Insituation for Engineering Research and publication (IFERP) heald on 30th & 31st December 2021 in Goa, Indi

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